Inflation-Targeting and Foreign Exchange Interventions in Emerging Economies

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Abstract

Inflation Targeting (IT) is a monetary regime theoretically associated to free floating exchange rate. However, monetary authorities' interventions on the foreign exchange markets are common place, particularly in developing economies. In this paper I propose a new method to assess inflation targeting emerging economies exchange rate flexibility. My approach combines the use of "indicator countries" to provide an empirical definition of exchange rate flexibility or rigidity, and clustering through Gaussian mixture estimates in order to identify a country's regime. Over the 18 emerging economies that have adopted inflation targeting, I've found that 10 of them have an as flexible exchange rate as the developed economies, while 4 have a managed float arrangement and the remaining 4 turn to have an exchange rate system as rigid as the standard peg currencies. My results show strong support to distinguish two different monetary regimes under inflation targeting: Flexible IT when the monetary authorities handle only one tool, the interest rate, and Hybrid IT when the monetary authorities add foreign exchange interventions to their tool-box. Last, I test empirically if exchange rate control has mattered during the 2007-2008 inflation shock. I find that hybrid inflation-targeting is strongly associated with a weaker inflation surge and less credibility loss.

Keyword: Monetary Policy, Foreign Exchange Interventions, Gaussian mixture model.

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1 Introduction

The exchange rate plays a larger role in monetary policy, both as a tool and as a target, for emerging economies than for advanced economies. This is du to the enhanced role of exchange rate channels in emerging economies, that are generally attributed to greater vulnerability to shocks, lower policy credibility, and underdeveloped domestic financial markets (see Stone et al. 2009). This prominent role of exchange rate in emerging economies' monetary policy is also associated to two phenomena: the "fear of floating" (Calvo & Reinhart 2002) and the "fear of appreciation" (Levy-Yeyati & Sturzenegger 2007). According to Cavoli (2009) the first phenomenon is justified by the fear of trade contraction due to higher exchange rate volatility, by an higher pass-through from exchange rate to domestic prices in emerging economies than in developed countries and by the balance sheet effects caused by currency mismatches and liability dollarization. Levy-Yeyati & Sturzenegger (2007) explain the second phenomenon by concerns about losing competitiveness. Also Aghion et al. (2009) demonstrate that exchange rate volatility reduces growth in countries with relatively less developed financial sectors.

Therefore, even if they do not set a particular target for the exchange rate, emerging economies monetary authorities are more concerned by the exchange rate than their counterpart in developed economies. This idea have been analysed by the literature as if emerging economies central bank should give more weight to exchange rate in their reaction function than developed economies. Hence, in the theoretical side, various models have been developed to explain under which circumstances it is justified for emerging economies central banks to use a Taylor rule augmented by the exchange rate[1], while in the empirical side a large number of papers have estimated such open-economy Taylor rules[2].

However, studies that analysis exchange rate policy only as a Taylor rule argument are missing the smoking gun: the most prominent policy is foreign exchange market interventions[3]. Surprisingly, foreign exchange intervention under inflation-targeting has not received much attention in the litterature[4]. The mains two reasons behind this are, first, macroeconomic models are not well suited to assessing the use of two instruments by one agent (both an interest rate instrument and foreign market intervention), and then, channel of foreign exchange market interventions is not yet clearly understood, neither empirically nor theoretically. However the need to address the foreign exchange market interventions is increasing, as central banking practices rely more and more on a "Two Targets, Two Instruments" principle[5].

[1] See Batini et al. 2003, Moron & Winkelried 2005, Cavoli & Rajan 2006, Yilmazkuday 2007, Cavoli 2008, Ravenna & Natalucci 2008, Restrepo et al. 2009, Roger et al. 2009, Stone et al. 2009, Bénassy-Quéré & Salins 2010 and Pavasuthipaisit 2010

[2] See Corbo et al. 2001, Mohanty & Klau 2005, Edwards 2006, Aizenman et al. 2011 and Frömmel et al. 2011

[3] As emphasized by Stone et al. (2009, page 25) "Foreign exchange interventions (...) is the main exchange rate policy implementation tool".

[4] With the notable exception of Berganza & Broto (2012) and Chang (2008).

[5] This was described by Ostry et al. (2012) as follows : "the central bank may opt for an IT regime, subordinating its monetary policy to achieving the inflation objective. If ,as the discussion above suggests,

This paper aims at filling a gap in the literature: it offers a method to assess emerging economies inflation-targeting central bank exchange rate policy. Based on the methodology developed by Levy-Yeyati & Sturzenegger (2005) to classify exchange rate arrangements, the flexibility degree of an exchange rate is defined by the join behaviour of its nominal exchange rate and the foreign exchange market interventions. Using a Gaussian mixture model, I compute the probability for any EEIT to have a floating exchange rate arragement, an intermediate system, or a fixed exchange rate system. The definition of each regime is assess by two pools of "indicator countries", from which data are randomnly selected to form a control sample in a bootstraping loop. My results show strong support to distinguish two inflation-targeting regimes : a flexible inflation-targeting regime, with flexible exchange rate, and an hybrid inflation-targeting regime under which the exchange rate is more controled and less flexible. Last, I test empirically if exchange rate controled have mattered during the 2007-2008 inflation shock. I find that hybrid inflation-targeting is strongly associated with a weaker inflation surge, less deviation from the target, and less credibility loss.

This chapter is organized as follows. Section 2 presents and discusses the regimes classification approach by **?**.Section 3 presents a new exchange rate arrangements classification approach, specifically designed to deal with inflation-targeting emerging economies. Section 4 considers weither exchange rate policy have mattered during the 2007-2008 inflation shocks. Section 5 briefly concludes.

emerging markets economies central banks also have available a second instrument (foreign exchange intervention), they can also limit temporary movements of the exchange rate without prejudicing attainment of their primary target, the inflation rate."

2 A focus on LYS classification approach

My purpose is to examine whether emerging economies implement similar inflation-targeting (IT) strategies than developed economies, or if these countries adopt particular policies, especially toward exchange rate flexibility. Is exchange rate as flexible in inflation-targeting emerging economies (ITEE) as in developed inflation-targeting economies, or is it less flexible, more controlled? Are foreign exchange interventions more frequent in ITEE than in developed IT economies, or of similar importance?

To answer, I propose an approach based upon the exchange rate arrangements classification litterature. The fear of potential gaps between officially reported and actually prevailing exchange rate regimes have given rise to the construction of alternative, *de facto*, classifications of exchange rate regimes that reflects actual rather than announced policies. Among the first and most influential papers, Calvo & Reinhart (2002) have shown that, in practice, many exchange-rate regimes do not function according to the *de jure* rules. This idea was already well accepted for fixed exchange rate arrangements, mostly after Obstfeld & Rogoff (1995) "Mirage of fixed exchange rate" paper. Many *de facto* classifications have followed, relying on a wide variety of econometrical and statistical methods. Therefore exchange rate classification methods have almost become a field of research by it-self, as described by Tavlas et al. (2008). One of the main results of that literature is the relativity of exchange rate definition: it is almost impossible to define an exchange rate regime such as fixed or floating only with thresholds or *ex ante* creterion. However it is always possible to define a regime relatively to the other regimes, and for example to consider that a group of countries is having a flexible exchange rate by the extend it has a more flexible exchange rate than the other groups. The approach developed by Levy-Yeyati & Sturzenegger (2005) (LYS) does pretty well in that way. They propose a purely statistical classification methodology, which does not rely on any *de jure* component that would come from an official source, or a threshold left up to the author's discretion. Economies are ranked or classified in relation to each other characteristics.

Among the various method developed in the litterature, LYS has the following charateristic. The number of currencies used by LYS to define a country's exchange rate is flexible: in the general case, one reference currency (the main trade and finance partner) is used, but if there isn't such an obvious reference currency or if a basket peg is known, a weighted exchange rate can also be used. The exchange rate series that are considered are the official one, and not those from the parallel or black market as in Reinhart & Rogoff (2004). Also, as long as the classification is not used to study bilateral trade, this seems to be fair (see Shambaugh 2004). Both the exchange rate and some exchange rate control instruments are used to defined a regime, as opposed to hard peg regimes studies such as Frankel et al. (2001) , Bénassy-Quéré & Coeuré (2002) and Bénassy-Quéré et al. (2006). The interest rate is let aside here, as opposed to Calvo & Reinhart (2002). LYS use the foreign exchange reserves to measure foreign exchange interventions as in Edwards & Savastano (1999), Reinhart (2000) and Edwards (2002). Their measure is a close substitute to the exchange market pressure proposed by Girton & Roper (1977) and used by Frankel & Wei (2008), Frankel & Xie (2009) and Frankel & Xie (2010). LYS method is purely statistical, similarly to Frankel & Wei (2008) and Frankel & Xie (2010). Thus it doesn't rely upon any *de jure* information, as in Ghosh et al. (1997), Eichengreen & Leblang (2003) and Dubas et al. (2005) or on the researcher judgment as in Bubula & Atker (2002).

LYS classification main features. LYS classification is built upon three variables: the nominal exchange rate volatility, the interventions in the foreign exchange market and the volatility of nominal exchange rate changes. Interventions in the exchange markets are measured through central banks' foreign reserves volatility. Idiosyncratic shocks may explain part of the nominal exchange rate changes. Therefore, a currency stability has to be measured by the volatility of its exchange rate related to reserves volatility. Volatility of nominal exchange rate changes is taken into account in order to consider policies with a medium term exchange rate target, achieved through a short term path. In such a procedure, called crawling peg, a currency's exchange rate is periodically adjusted, but the exchange rate may remain fixed between one change to the next. Therefore, exchange rate volatility does not imply volatility of nominal exchange rate changes, as opposed to what is observed with a free floating exchange rate.

Every variable is expressed in yearly average (of monthly data) and then is z-normalized. Thus, any observation is a three-dimension object (one dimension for each variable) related to a given country and a given year. Then they group similar observation into clusters. This step is done with the K-means partitioning algorithm. This method, based on nearest centroid sorting, assigned individual cases to the cluster with the smallest distance between the case and the center of the cluster.

	$\sigma(e)$	$\sigma(\Delta e)$	$\sigma(r)$
Flexible	High	High	Low
Crawling Peg	High	Low	High
Fixed	Low	Low	High
Dirty float	High	High	High
Inconclusive	Low	Low	Low

Table 1: LYS classification criteria

Then, they associate each cluster to an exchange rate regime. They assume: "the cluster with high volatility of reserves and low volatility in the nominal exchange rate identifies the group of fixers. Conversely, the cluster with low volatility in international reserves and substantial volatility in the nominal exchange rate corresponds to countries with flexible arrangements" (LYS 2005, p 1605). The group with high volatility in the nominal exchange rate and international reserves but low volatility of nominal exchange rate changes stands for countries with "crawling peg" . To these three groups, they add a fourth one "dirty float", which "should be associated to the case in which volatility is relatively high across all variables, with intervention only partially smoothing exchange rate fluctuations." (LYS 2005, p 1606). Last, the cluster in which every variable have low values, is called "inconclusive" and they deal with it with in a second clustering round.

Strengths and weaknesses LYS classification method has three main virtues, as compared with other methods. First virtue: exchange rate movements and foreign exchange interventions are considered relatively to each other. Second virtue: it is a purely *de facto* classification. It does not rely on any *de jure* component that would come from an official source, or any component left up to the author's discretion[6]. Third virtue: LYS classification is based on *relative* definitions, as opposed to an *absolute* definitions, which would be based on some thresholds or some specific *a priori* (*ex ante*) measurements. Thus, in there classification scheme, a country's group is labeled as "floating" (for instance) only by the extend it floats more than the other groups. Because the message delivered by the "fear of floating" literature is precisely that there is no right absolute definition, this is a major feature to properly define exchange rate systems.

Though LYS regimes classification has become a standard in exchange rate policies studies, there are nevertheless some limitations that must be taken into account when examining it.

Firstly, LYS' classification ends in 2005, and thus badly covers years of IT experiences (which will be our focus in next section). Secondly, and more importantly, LYS way to deal with the "inconclusive" cluster is not persuasive. This cluster contains 1798 observations over 2860 (one observation is given by the average of the three variables over one year for one country). Therefore, more than 60% of the observations are not associated to a policy regime and are pass by during the first round. To solve the issue, LYS run a second time the k-means partitioning algorithm. This means they apply the same method used for the whole sample during the first round on the single inconclusive group. This two rounds approach has two main caveats. Firstly, after the second round, 698 observations are (again) grouped into an "inconclusive" cluster, not associated to a policy regime. Hence, 25% of the initial data set is simply left aside. This is a pretty large amount, and thus may make impossible to use

[6] As emphasized by the authors: *Previous exchange rate classification attempts to correct the misclassification of the standard* de jure *approach relied on some chosen criteria. Ghosh et al. (1997), for example, excluded from the fix group those* de jure *fixes that changed the parity more than once over a year. As a result, the final outcome in those cases depended on the researcher's discretion in the definition of these criteria (for example, whether he chooses to exclude from the fix category those countries that realign only once, or more than twice). In addition, they required a priori definitions that are not always immediately obvious. For instance, does the size of the devaluation matter and, if so, how? Moreover, how can we distinguish between a devaluation that is a deliberate policy decision in the face of increasing market pressure (a behavior closer in nature to a float) and a devaluation that is the result of an massive but ultimately unsuccessful attempt to defend the fixed parity (which will be closer to a fix)? In this regard, cluster analysis has the advantage of avoiding any discretion from the researcher beyond that required to determine the classifying variables and to assign clusters to different exchange rate regimes, once they are identified by the procedure.* Levy-Yeyati & Sturzenegger (2005, page 1610).

the out-coming classification for some purpose. One may also ask why do not they run a third round. Secondly, there is no convincing argument that allows to think that observations labelled in the first round (for instance "dirty float") are similar to those that received the same label in the second round. This clearly appears while looking at the two rounds clusters boundaries. Are the clusters produced from the two rounds really covering the same policy realities? This is a major doubt one may have about LYS classification. It seems to me that the "inconclusive" cluster issue is partly due to the extremely large time period and country coverage chosen by the authors. Their data set covers any country included in the IMF statistic from 1973 to 2005. Hence it covers a wide variety of realities, and includes a large number of (positive and negative) outliers. On the other hand even if they left out barely 1 over 4 observations, which such a large coverage they obtain an interesting and useful classification, seen as a standard in the litterature.

Last, LYS use the k-means algorithm to group the observations into consistent clusters. This is standard algorithm in the partitioning literature. However it is known to have some drawbacks. First drawback, the number of clusters, k, is an input parameter that has to be defined *ex ante*. Therefore, it is not exact to say: *"cluster analysis has the advantage of avoiding any discretion from the researcher beyond that required to determine the classifying variables and to assign clusters to different exchange rate regimes, once they are identified by the procedure"* Levy-Yeyati & Sturzenegger (2005, page 1610). The researcher also has to choose how many groups he would like to divide his observations into. In LYS' case, their method consist in assuming that there are 5 exchange rates regimes (Flexible, Dirty float, Crawling peg, Fixed and Inconclusive) and then to compose the desired groups with the K-means algorithm. Hence, the algorithm is used only for grouping different observations into similar clusters, but that algorithm does not deliver any information about the k number goodness-of-fit or on the grouping quality of the clusters formed.[7] Second drawback: k-means may converge to a local minimum. Thus it may produce bad results and it may be extremely sensible to the initalisation parameters (the first observations used as centroid). Last, some have argue (see Hennig 2011) that k-means tend to produce clusters of similar size. This is due to the cluster mode, which is based on spherical clusters that are separable in a way so that the mean value converges towards the cluster center.

[7]Since an inappropriate choice of k may yield poor results, it is important, when performing k-means, to run diagnostic checks for determining the number of clusters in the data set. LYS (2005) went fast on that topic.

3 An original method to assess exchange rate control

3.1 The method

My purpose is to examine whether emerging economies implement similar IT strategies than developed economies, or if these countries adopt particular policies, especially toward exchange rate control through foreign exchange intervention. Therefore, I propose a new classification method, specifically designed to assess the degree of flexibility of ITEE currencies.

Two control samples. I consider that two fundamental elements of LYS method are good and are to be kept to develop my own approach: the three variables used, and the clustering procedure. I focus on EEIT. Therefore, these countries will constitute the core of my data sample. However, a good classification of exchange rate arrangements has to be a *relative* classification[8]. Therefore, in order to access the exchange rate arrangement of inflation-targeting emerging economies, I have to analysis their exchange rate flexibility relatively to those of some other economies. These control samples are hereafter called “indicator countries”. They constitute the counterfactual economies. Actually, I need two control samples, one for each polar policy: flexible and rigid arrangements. The flexible arrangement control sample is made of developed IT economies. These economies are the benchmark of inflation-targeting frameworks associated with a flexible exchange rate regime. Hence, it shows if inflation-targeting emerging economies exchange rates are as much flexible as developed IT economies exchange rates are. The fixed arrangement control sample is made of economies that have rigid regimes. Finally, my database is the sum of ITEE observations plus the rigid and flexible indicator countries samples.

Partitioning algorithm. I apply on that database a partitioning algorithm to split the whole set of observations into consistent groups. I shown in next section, page 5, the superiority of a Gaussian mixture approach over the k-means algorithm used by LYS. Data are split according to their likelihood to belong to a given Gaussian distribution. All the observations belonging to a Gaussian form one cluster (or one group). Each distribution is then assumed to be produced by a unique process, which, in turn, is assumed to be a given exchange rate regime. The optimal number of clusters as well as the cluster composition is given by a statistical criterion, and, then, each cluster is associated to an exchange rate policy.

Labeling policies. The indicator countries are used to label the groups, and thus to associate a cluster to a monetary policy. For instance, in case the outcome is two clusters, all observation in the group where the majority of floating exchange rate indicator countries are,

[8] As opposed to an *absolute* classification, which would be based on some thresholds or some specific measurements.

are labelled as of *de facto* floating. Hence, any observation from an emerging IT economy that is included in that group will be considered as *de facto* floating. The outcome being generally higher than two groups, an “intermediate” regimes has also to be considered. The Gaussian model estimation gives the probability for any observation to belong to any cluster. This probability is therefore the probability for a given country at a given date to have a given policy.

Robustness. An important drawback of partitioning algorithms is their sensibility to data composition: a slight change in the data may have a large impact on the results. This is particularly true in the case of outliers. To address this issue and insure the results' stability, I propose a boot-strapping approach, with random sampling. At every iteration steps, the inflation-targeting emerging economies observations remain in the data set, but the two sets of indicator countries change. The sets of indicator countries used for a given partition are randomly selected among all control observations, with respect to the two types of indicator countries (fixed and floating). Therefore, the partition is done over a set of observations consisting in the inflation-targeting emerging economies plus some randomly picked up fixed indicator countries' observations plus some randomly picked up floating indicator countries' observations. At any iteration I compute the probability for an EEIT observation to belong to any policy. My final result is the average of every iterations' probabilies, that is the average of more than 50000 partitions' outcomes. Thus its stability is insured.

3.2 Partitioning through Gaussian mixtures

In order to cluster the observations into consistent group, I estimate a Gaussian mixture model.

Gaussian mixture definition: Let us think of the k groups obtained with the k-means clustering method by LYS. One can suppose that there is a Gaussian centered at each of the means. Thus each cluster can be characterized by a density function, and the overall data set can be described by a mixture of all the density functions (plus the probability for a given observation to belong to one of them). This can be done through a Gaussian mixture model.

The univariate Gaussian distribution can be writen as

$$p(x|\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) \tag{1}$$

where the mean $\mu \in \mathbb{R}$ and the variance $\sigma \in \mathbb{R}^+$ are the parameter of the distribution.

In our case we have three variables per observations (the nominal exchange rate volatility, the interventions in the foreign exchange market and the volatility of nominal exchange rate changes) thus we are in a trivariate case. Thus, the Gaussian distribution as to be extended to more than one distribution. The multivariate case can be written as

$$p(x|\mu, \Sigma) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right) \tag{2}$$

where d (equals 3) is the number of distributions. In the multivariate case the mean is a vector, $\mu \in \mathbb{R}^d$, and the covariance is a positive definite matrix, $\Sigma \in \mathbb{S}^d$.

For a given set of m observations, $x = \{x_1, ..., x_M\}$ that are assumed i.i.d and drawn from a multivariate Gaussian, the log-likelihood is given by

$$p(x|\mu, \Sigma) = -\frac{Md}{2} log(2\pi) - \frac{M}{2} log|\Sigma| - \frac{1}{2}\sum_{m=1}^{M}(x_m - \mu)^\top \Sigma^{-1}(x_m - \mu) \tag{3}$$

By definition, a Gaussian distribution is unimodal, which may not the case for any given dataset, particularly when the dataset is to be divided into K clusters. Thus the combination of these K Gaussians into a Gaussian Mixture Model is to be considered. To do so, one more parameter has to be introduced: the mixing coefficient, denoted by $\pi \in \mathbb{R}^K$. Any π_k satisfies $\pi_k \geq 0$ and $\sum_{k=1}^{K} \pi_k = 1$. The Gaussian mixture model is then given by:

$$p(x|\pi, \mu, \Sigma) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \tag{4}$$

where $\mu = \{\mu_1, ..., \mu_K\}$ and $\Sigma = \{\Sigma_1, ..., \Sigma_K\}$ are the mean and variance of the respective Gaussian distribution ($\mathcal{N}$, as in equation (2)). [9]

The log-likelihood associated to this model (for m points, assuming independance) can be written as

$$log \;\; p(X|\pi, \mu, \Sigma) = \sum_{m=1}^{M} log \sum_{k=1}^{K} \pi_k \mathcal{N}(x_m|\mu_k, \Sigma_k) \tag{5}$$

Once the parameters estimates have been obtained, the *a posteriori* probability that an observation m belongs to the group k can be deduced:

$$\pi_{m,k} = \frac{\pi_k \mathcal{N}(x_m|\mu_k, \Sigma_k)}{\sum_{k'} \pi_{k'} \mathcal{N}(x_m|\mu_{k'}, \Sigma_{k'})} \tag{6}$$

In our case, $\pi_{m,k}$ is the probability that an observation m, for example Brazil in 2010, belong to a group k, for example free floating exchange rate arrangement. Thus the sum of $\pi_{m,k}$ over k equals 1, with k' being in that example fixed or intermediate exchange rate arrangement.

[9] Since the observations are assumed to be independently distributed, equation (4) may be written as: $p(x|\pi, \mu, \Sigma) = \prod_{m=1}^{M} \sum_{k=1}^{K} \pi_k \mathcal{N}(x_m|\mu_k, \Sigma_k)$

Variance decomposition: This general expression of the Gaussian mixture model allows some sophistication. In particular, the covariance matrix can be decomposed into sub-variables on which a large set of constraints can be applied.

Following Banfield & Raftery (1993) a spectral decomposition of the covariance matrix is given by:

$$\Sigma_k = \lambda_k D_k A_k D_k^\top \tag{7}$$

for $k = 1, ..., K$ and where

- $(\lambda_{k1}, ..., \lambda_{kd})$ are the matrix eigenvalues with $\lambda = \Pi_{m=1}^{d}(\lambda_{mk})^{1/d}$.
- D_k is the matrice of eigenvectors .
- A_k is a diagonal matrix whose elements are proportional to the eigenvalues, that is $A_k = \frac{1}{\lambda_k}$ diag$(\lambda_{k1}, ..., \lambda_{kd})$ and det$A_k = 1$.

This decomposition of Σ_k allows to charaterize the distribution. In particular, D_k gives the orientation of the the covariance matrix, while A_k determines the shape of the density contours. Last, λ_k specifies the volume of the corresponding ellipsoid (or hypervolume). The three characteristics of distributions, that is orientation, volume and shape, can be estimated from the data, and can vary between clusters, or be constrained as the same for all clusters

Table 2: Possible parameterizations of the covariance matrix Σ_j for multidimensional data.

Model name	Form	Distribution	Volume	Shape	Orientation
EII	λI	Spherical	Equal	Equal	NA
VII	$\lambda_j I$	Spherical	Variable	Equal	NA
EEI	λA	Diagonal	Equal	Equal	Coordinate axes
VEI	$\lambda_j A$	Diagonal	Variable	Equal	Coordinate axes
EVI	λA_j	Diagonal	Equal	Variable	Coordinate axes
VVI	$\lambda_j A_j$	Diagonal	Variable	Variable	Coordinate axes
EEE	$\lambda D A D^T$	Ellipsoidal	Equal	Equal	Equal
EEV	$\lambda D_j A D_j^T$	Ellipsoidal	Equal	Equal	Variable
VEV	$\lambda_j D_j A D_j^T$	Ellipsoidal	Variable	Equal	Variable
VVV	$\lambda_j D_j A_j D_j^T$	Ellipsoidal	Variable	Variable	Variable

Source: Fraley & Raftery (2007, page 8).

Celeux & Govaert (1995) have discribed the different model that can be obtained by constraining the orientation, volume and shape of the covariance matrix. Authors also provide details of the EM algorithm for maximum likelihood estimation for these models. Fraley et al. (2012) (see also Fraley & Raftery 2007) proposed a computational methodology for some of them. I willl focus on the multidmensional case, considering three options : to be equal among clusters, to vary among clusters, to be given by the identity matrix. Fraley et al. (2012) proposed a denomination of all these (sub-)models as a three letters code: 1 letter to describe each of the 3 main charateristics.[10] For example, EVI denotes a model in which the volumes of all clusters are equal (E), the shapes of the clusters may vary (V), and the orientation is the identity (I). Clusters in this model have diagonal covariances with orientation parallel to the coordinate axes. The different model of the covariance matrix for which a computational method is known are summarized in Table 3.2. I will keep refering to this name system in the section dedicated to the results, in particular see Graph B.3 page 46.

A criterium to choose the number of clusters: The choice of the number of components has to be done according to the quality of the fit of the estimated density and the detection of distinct groups. A particularly simple and viable method consists in choosing the value of K which minimizes the Bayesian Information Criterion (BIC), as difined by Schwarz (1978).

$$BIC = -2\,\widehat{l} + w\ log\ n \tag{8}$$

where $\widehat{l}$ is the estimated log-likelihood, n is the number of observations, and the term w corresponds to the number of parameters to be estimated ($w = 3K - 1$) in the bivariate case.

From k-means to Gaussian mixture I show in Appendix A page 35 how the Gaussian mixture that I use differ from the K-means alogorithm used by **?**. Indeed, LYS' k-means is similar to the Gaussian, but it supposed two limitations: the covariance matrix is constraint, and the probability to belong to a group is not computed. Therefore, the constraint on the covariance matrix gives to their clusters a spherical shape, and all clusters are being of similar size. Also, in their approach, the probability for an observation to belong to a group is not computed. An observation either belong to a group or not. Whereas in my approach the clusters' shape is flexible, and a precise probability to belong to a group is computed. All in all, the Gaussian mixture approach seems more flexible and robust than those with k-means.

[10] I refer to these models names in the section dedicated to the results. In particular, see Graph B.3 page 46.

4 Results

4.1 Data

My data set includes 75 countries, which is composed of 27 IT countries, consisting of 18 emerging economies and 9 developed economies. I use the list of IT countries defined by the Bank of England in a work (see Hammond 2009, and Hammond 2012), based on a broad set of indicators, and very well documented. To define the rigid regimes indicators countries, I follow the IMF classification (see "Classification of Exchange Rate Arrangements and Monetary Policy Frameworks", IMF website). I consider two items: "currency board arrangements" and "other conventional fixed peg arrangements against a single currency"[11]. I obtain 47 indicators countries for the fixed exchange rate benchmark. Information about the data set is summarized in Appendix B.1 page 38. The number of floating indicators and rigid indicators is balanced through the boot-strapping method, which allows using similar sub-samples.

I use monthly data form IMF's International Financial Statistics, over the period 1990-2012 (this is the wider range possible since the first country which adopted IT, New-Zealand, did it in December 1989). I fallow Levy-Yeyati & Sturzenegger (2003) and Levy-Yeyati & Sturzenegger (2005) for the definition of the three variables:

- Exchange rate volatility (σe), measured as the average of the absolute monthly log changes in the nominal exchange rate relative to the relevant anchor currency over the year.
- Volatility of exchange rate changes ($\sigma_{\Delta e}$), measured as the standard deviation of the monthly log-change in the exchange rate.
- Interventions in the exchange markets, measured as central banks' foreign reserves volatility (σr), that is the average of the absolute monthly log-change in dollar denominated international reserves relative to the log-change in the value of the monetary base.

See Appendix B.2 for a complete description of variable computation. Every variable is expressed in yearly average (of monthly data) thus an observation is a three dimension object related to a given country and a given year, in the (σe , $\sigma_{\Delta e}$, σr) space.

Random sampling After computation of the three variables, I left out observation if I lack data for at least one of the classifying variables. I also left out IT countries' observation for

[11]There are plenty of different rigid exchange rates families. My fixed exchange rates control sample takes a broad definition. It includes a lot of countries having various degrees of rigidity. Therefore, the robustness and stability of my result is insured through the boot-strapping estimation method.

the years before IT implementation. I obtain 757 country-year data points: 89 for floating exchange rate indicators countries, 490 for fixed exchange rate indicators countries, and 178 for the inflation-targeting emerging economies.

The different sizes of the two control sample is not a problem, becuase it will be corrected by a repetitive random sampling process. This approach consists in estimating the Gaussian mixture model many times, each time with a different counterfactual sample, composed of observations randomly picked up among the two indicator countries' data sets. Hence, the Gaussian mixture model is estimated on a sample made of all points for inflation-targeting emerging economies, and $2x$ points for indicators countries, among which x points are randomly chosen among floating exchange rate indicator countries' observations, and x points are randomly chosen among the fixed exchange rate indicator countries' observations. Last, x takes any value from 60 to the size of the smallest indicator countries sample. Finally, the process is done after more than 50000 iterations. In other words, the Gaussian mixture model is estimated with more than 50000 different data samples.

4.2 Three exchange rate flexibility degrees: floating, intermediate and fixed.

The classification process is based on the following loop:

1. Random composition of the control sample.
   A given number of observations are randomly selected among the two sets of indicator countries in order to compose the control sample. Added to the EEIT observations, they compose the data set for one iteration.

2. Gaussian mixture model estimation.
   The Gaussian mixture model is estimated. The BIC criterion maximization gives the best variance-covariance decomposition model and the optimal number of Gaussians that are mixed into the model (see Graph B.3 page 46). Only the optimal distribution is taken into account . The probability for any EEIT observation to belong to any Gaussian is computed.

3. Exchange rate arrangements classification.
   All observations belonging to one Gaussian are assumed to form one group (or cluster). That cluster is then assigned to an exchange rate regime according to the indicator countries' position. The probability for any EEIT observation to belong to any Gaussian can now be read as the probability to have a monetary regime.

The main result of step 2 is that the optimal partitioning is three Gaussians in most of the case. Therefore, three exchange rate flexibility degrees are considered in step 3: fixed, floating and intermediate. For instance, if the majority of a Gaussian's elements are coming from the floating exchange rate indicator countries, hence that Gaussian is label as "*de facto* floating exchange rate arrangement", and the probability for any observation to belong to that Gaussian is seen as the probability to have *de facto* a floating exchange rate arrangement. The same reasoning holds for fixed exchange rate arrangement. The remanding group is labelled as "*de facto* intermediate exchange rate arrangement", and stands for managed floating or "dirty-float" regime. It may also happen that the BIC criterion maximization gives 2 or 4 gaussians, and the exact algorithm used to label the clusters is presented in greater detail in Appendix (B.3). Finally the process described above is repeated thousands of times, with different indicator countries samples, randomly composed, and the final result is for any observation the average probability over evey iteration.

Results are given in Appendix B.5 page 58. For instance, Chile in 1999 has a probability of 96% to have a floating exchange rate according to Table B.5 (page 60). Consistently, Chile in 1999 has a probability of 2% to have a fixed exchange rate (page 58) as well as a probability of 2% to have an intermediate exchange rate arrangement (page 59). The exact reading is: the probability of Chile's exchange rate to be as flexible as developed IT economies exchange rate is 96%, while the probability of Chile's exchange rate to be as much controled as fixed exchange rate economies is 2%. This does not mean that Chile never try to control its exchange rate or that foreign exchange market intervention never happen in Chile. Chile's monetary authorities may proceed to FX intervention. But our result indicates that if they do proceed to FX intervention, they do it by the same extend than developed IT . Similarly, Turkey exchange rate arrangement in 2012 has a probability of 90% to be considered as "floating", a probability of 10% to be seen as "intermediate", and a zero probability to be classified among the "fixed" exchange rate economies.

Focusing on the most probable regime for each year, Table 4.2 page 17 summarized for all countries the number of years associated to each degree of flexibility. Over all the years of IT experience in emerging economies, the most common practice was free floating, which represents 60% of the observations (106 observations over a total of 178). The last 40% are equally distributed between managed float (the intermediate policy, 20%, 34 observations over 178) and fixed exchange rate (20%, 38 observations over 178).

Table 3: Exchange rate arrangements occurrences

	Number of years with			Years Covered
	Fix	Intermediate	Float	
ALBANIA	2	0	1	3
ARMENIA	0	1	5	6
BRAZIL	0	9	2	11
CHILE	0	3	10	13
COLOMBIA	2	3	8	13
CZECH REP.	3	0	10	13
GHANA	1	3	1	5
GUATEMALA	5	0	2	7
HUNGARY	0	2	9	11
INDONESIA	1	1	6	8
MEXICO	0	2	9	11
PERU	5	0	3	8
PHILIPPINES	5	0	5	10
POLAND	0	3	10	13
ROMANIA	4	0	3	7
SERBIA, REP. OF	0	1	6	7
SOUTH AFRICA	0	6	6	12
THAILAND	6	1	6	13
TURKEY	0	3	4	7
Total	34	38	106	178

Exchange rate flexibility degree counts are based on the most probable regime for a country for a given year.

The fact that most observations are floating exchange rate was expected. Theoretically, the definition of inflation-targeting implies to focus only on price stability and, therefore, to let the exchange rate float. Also, finding that 40% of the observations does not match to floating exchange rate is not surprising: a large literature has shown that monetary authorities try to reduce exchange rate volatility, most notably in emerging economies. This is the well-known "fear of floating" phenomenon. However, among the non-floating observations, the share of the most rigid, 20%, is high. One over five ITEE exchange rate observations is as much rigid as exchange rate with a peg. Theoretically, the reality of inflation-targeting under such circumstances should be question. Therefore, two distinct inflation-targeting regimes should be considered, according to the role played by the exchange rate: flexible inflation-targeting and hybrid inflation-targeting.

4.3 From flexibility degrees to IT regimes

Flexible inflation-targeting corresponds to the textbook definition: a monetary framework under which price stability is explicitly recognised as the main goal of monetary policy. Further more, in such a framework, Tinbergen's principle holds: the central bank has one objective and, therefore, one and only one instrument, the interest rate. I use the word "Flexible" inflation-targeting because under such a framework, the exchange rate is flexible. However, “Flexible” inflation-targeting also refers to Svensson’s definition of inflation-targeting: *“Flexible inflation-targeting means that monetary policy aims at stabilizing both inflation around the inflation target and the real economy, whereas strict inflation-targeting aims at stabilizing inflation* only, *without regard to the stability of the real economy, what Mervyn King (1997) has described as being an “inflation nutter”. ”* in Svensson (2010, page 1). In my view, since “strict” inflation-targeting is only a theoretical frame, “flexible” inflation-targeting should be seen as the baseline. That’s why I call flexible IT standard IT with flexible exchange rate.

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Proposition: Under *Hybrid Inflation-Targeting*, aside its official goal and its official tool, respectively the price stability and interest rate setting, the central bank aims at managing the exchange rate through exchange market interventions[12].

Therefore, a country whose exchange rate arrangement is most probably floating is assumed to have a flexible inflation-targeting regime, otherwise the country is considered to be under hybrid inflation-targeting regime. The resulting classification is given in page 61, and summarized in Table 4.3.

[12]Hybrid Inflation-targeting regimes is also the title of a paper by Roger et al. (2009). In this paper the authors examine whether including the exchange rate explicitly in the central bank‘s reaction function can improve macroeconomic performance using a DSGE model. They call Hybrid inflation-targeting regimes, those where the central bank reacts to the exchange rate or control the exchange rate, as opposed to “plain vanilla IT” .

Table 4: Inflation-targeting regime based on exchange rate flexibility degree.

	Arrangement probability			IT regime
	Fix	Intermediate	Float	
ALBANIA	69	0	31	Hybrid
ARMENIA	7	20	74	Flexible
BRAZIL	6	63	30	Hybrid
CHILE	6	19	75	Flexible
COLOMBIA	15	21	64	Flexible
CZECH REP.	27	8	65	Flexible
GHANA	17	51	32	Hybrid
GUATEMALA	58	10	32	Hybrid
HUNGARY	11	31	58	Flexible
INDONESIA	23	15	62	Flexible
MEXICO	12	22	66	Flexible
PERU	54	7	39	Hybrid
PHILIPPINES	44	9	47	Hybrid
POLAND	6	26	68	Flexible
ROMANIA	48	6	46	Hybrid
SERBIA, REP. OF	12	22	66	Flexible
SOUTH AFRICA	3	36	62	Flexible
THAILAND	36	15	49	Hybrid
TURKEY	2	38	60	Flexible

5 Does exchange rate control improve inflation-targeting in emerging economies?

I have established that there are two different inflation-targeting (IT) frameworks applyied by emerging economies: inflation-targeting with free floating exchange rate, and inflation-targeting with managed float. I call the first framework flexible inflation-targeting (FIT) and I call the second framework hybrid inflation-targeting (HIT).

I want to test empirically whether or not exchange rate management improves inflation-targeting, that is, does exchange rate management help the central banks to achieve their targets? Does it impact the central banks' credibility? Does it reduce the Taylor curve output/inflation volatility trade-off? In response to these questions, I analysis the reaction of inflation-targeting emerging economies (ITEE) to the 2007-2008 inflation shock. This shock is a perfect example of an exogenous shock on prices that appeared on a worldwide scale. Furthermore, inflation-targeting is a recent monetary policy framework; it was adopted by central banks during the early 2000s. Thus, it was the first price shock that these central banks had to deal with. This section is structured as follows. Subsection 5.1 presents some stylized facts on the 2007-08 inflation shock. In Subsection 5.2, I describe my methodology and data. Section 5.3 sets out my results. The final section provides a brief conclusion.

5.1 The inflation shock that ended the great moderation

The sharp increase in inflation that began in 2007 was the first big shock central bankers faced since they adopted inflation-targeting strategies. Indeed, the shock ended the "Great Moderation". Consummer price inflation followed from the soaring prices of energy, raw materials and food products. Moreover, inflationary pressures have been particularly challenging in emerging countries, where the share of food and energy consumption is high. The development of Moody's Commodities Index shows the magnitude of the shock.

This index aggregate the prices in U.S. dollar of energy and metals, of food products like coffee, cocoa, sugar, etc (36 %) and of grain (28%) . It increased by 28 % between the third quarter of 2007 and third quarter of 2008. During that period, inflation had increased sharply in all countries: it averaged 9.3 % in Latin America, 11.6 % for the countries of Eastern Europe, 9.5% for Asia and 16 % for the Middle East

In this context, prices have increased at higher rate than targeted. Only Brazil has met its target and fulfilled its commitments. In reaction to such a failure, Turkey and Guatemala decided to revise upwards their official inflation targets. Hence, Turkey's inflation goal moved from 4% to 7,5% (The objective was set to 7,5% for the year 2009, 6,5% for 2010 and 5,5% for 2011) and Guatemala enhance its inflation target by 0.5 percentage point, from 5% to 5.5%. Guatemala also wider its target range form 1% to 1.5%. In South Africa, the government suggested proceeding to such an inflation target adjustment, but that was rejected by the central bank attempting not to loose credibility credibility. All central banks had increased their interest rates. While some have made a slight move, such as Thailand whose key interest rate merely increased by 25 bp, most countries have chosen to quickly and firmly tighten policy. Such, for example, is the case of Poland and Chile whose interest rate increased by 200 and 250 bp respectively from April 2007 to August 2008. Lastly, some economies have also turn to non-conventional policies: Colombia have increased reserves requirements and Peru have strengthened controls on capital flows

5.2 Diffs-in-diffs analysis

Method

I want to determine how exchange rate controls added to the inflation-targeting framework affects dimensions of economic performance such inflation, output growth and interest rates. I compare the performance of the FIT countries with that of the HIT countries during the 2007-2008 price shock to determine whether or not control matters. Suppose, I am interested in how exchange rate management affects a variable X, say inflation. I assume that X_{it}, the value of X in country i and period t, is given by

$$X_{it} = k + \alpha Q_t D_i + \mu_i + \eta_t + v_{it} \tag{9}$$

where k is a constant, μ_i is a country-specific effect, η_t is a period-specific effect, v_{it} is an error term specific to country i in period t, Q_t is a dummy variable equals zero in normal time and one during the 2007-2008 price shock, and D_i is a dummy variable taking a value of zero if the country is FIT and a value of one if the country is HIT.

I estimate this equation 9 using the standard "differences in differences" approach, as defined by Ball & Sheridan (2004). Differencing equation 9 over time leads to equation 10. The *pre* subscript indicates the time period before 2007-2008 inflation shock, and the *post* subscript indicates the time period during the shock: $Q_{pre} = 0$ and $Q_{post} = 1$. Following Maddala (1989), Ball & Sheridan (2003) page 18 and Goncalves & Salles (2008) one can show that the correlation between the benchmark *pre*-period variable and the dummy variable, as well as the mean reversion problem are solved by adding the initial value of X to the right side of equation 10. Thus, I obtain an estimator of equation 9 given by equation 11 which measures the difference in the average inflation rate (for instance) between the two time periods (*post* minus *pre*) as the function of the IT framework (dummy variable D) and the average inflation rate of the *pre*-shock period's average inflation.

$$X_{i,post} - X_{i,pre} = a_0 + a_1 D_i + \epsilon_{it} \tag{10}$$

$$X_{i,post} - X_{i,pre} = a_0 + a_1 D_i + a_2 X_{i,pre} + \epsilon_{it} \tag{11}$$

Data and time periods

In this section I compare the performance of FIT with HIT. The question I raised - does exchange rate control improve inflation-targeting in emerging economies? - being precisely focused on the emerging economies that have adopted an inflation-targeting framework, I used the same sample of ITEE as in section **??** page **??** (and the ITEE sample only) [13]. See annex xxx for more details.

To have a good benchmark, the *pre*-period range from the first quarter of 2002 to the last quarter of 2006. I can not start the *pre*-period before 2002 because only a few emerging economies were inflation targeters in the early 2000s. Furthermore, the first few years of IT are generally years of transition from high to low inflation (see (Restrepo et al., 2009)). Thus, a wider *pre*-period would limit the sample to fewer countries and would include more outliers. The *post*-period basicaly covers the two years of high inflation rates. It starts in the first quarter of 2007, when the inflation pressures appeared (see Jàcome et al. (2009)). The *post*-period ends in 2008 in order not to include the consequences of Lehman's bankruptcy and the financial crisis aftermath.

I used quarterly data from IMF's International Financial Statistics and Data-Stream. Among the 19 ITEE covered by my exchange rate arrangements classification, 2 of them have adopted inflation-targeting too late to be covered consistently during the two periods: Albania and Ghana (who have adopted IT in 2009 and 2007 respectively). As a result my database covered 17 countries, with 32 quarters for the 10 longest IT experience countries (Brazil, Chile, Colombia, Czech Republic, Hungary, Mexico, Philippines, Poland, South Africa and Thailand) and 16 quarters for the last to join before the shock (Armenia and Serbia). I have tested many different settings and the results are robust. Most notably they are robust to change in the definition of the *pre* and *post* periods. Robustness checks with different *pre* and *post*-period samples are presented in Appendix **??**.

[13] In the previous section, I compared the emerging economies that target inflation with developed economies and with countries having a fixed exchange rate arrangement, whereas in this section the comparison is among the emerging economies that target inflation.

5.3 Results

Taylor principle

Table 7 page 28 reports my results for the real interest rate. The estimation of equation 10, with X denoting the real interest rate (Table 7, antepenultimate column), shows that on average the FITs real interest rate dropped by more than 100 bp (constant $\alpha_0 = -1.36$, p-value$< 1\%$). The dummy variable was associated with a positive but not significant coefficient ($\alpha_1 = 0.97$, p-value$> 10\%$), meaning that the real interest rate of HITs failed in the same proportion as it did for FITs. Equation 11 (last column in Table 5) reveals that this drop in the real interest rate is not correlated with the *pre*-period level (X_{pre} is associated to coefficient $\alpha_2 = -0.07$, p-value $> 10\%$). Central Banks that had low real interest rates before the shock did not react faster or stronger than the others.

The results above were not expected. In the two groups of countries, the decline in the real interest rate shows that CBs did not raise their nominal rates faster than inflation. Thus, none of the monetary authorities applied the so-called Taylor Principle.

The interest rate setting under inflation-targeting is generally assumed to follow a simple Taylor rule. This rule is a simple description of the complex mechanism that leads central banks to set interest rates. The standard Taylor rule is

$$i_t = i^* + \beta(\pi_t - \pi^\star) + \gamma x_t + \epsilon_t$$

where i_t is the central bank's policy interest rate, i^* is the long-run policy rate, π_t is inflation, $\pi^\star$ is the central bank's inflation target, x_t is output gap, and ϵ_t is a random variable. Taylor (1999) uses this equation to interpret Federal Reserve behaviour from the 1960's to the 1980's with settings of $\beta = 1.5$ and $\gamma = 0.5$ or 1. The Taylor principle is the requirement that a sustained increase in the rate of inflation must eventually result in an increase in the nominal interest rate of an even greater size. This leads to constrain the parametrization of the Taylor rule to a setting with $\beta > 1$. Most importantly, the Taylor rule results in determinacy if and only if it respects the Taylor principal. This has been shown theoretically for the standard new-keynesien model by (Woodford, 2003) among others and empirically tested by Lubik & Schorfheide (2004) or Teles & Zaidan (2010). As emphasised by Davig & Leeper (2007) (page 607) the failure of monetary policy to satisfy the principle can produce two undesirable outcomes: *First, the effects of fundamental shocks are amplified and can cause fluctuations in output and inflation that are arbitrarily large. Second, there exist a multiplicity of bounded equilibria in which output and inflation respond to non-fundamental sunspot disturbances.* My results suggest that none of the central banks applied the Taylor Principle. Other papers, like Teles & Zaidan (2010) among others, reach the same conclusion in the case of emerging economies. Low political feasibility, central bankers' lack of willingness, or simply a complex economic agenda may be as much arguments not to raise too high the interest rate. However, this outcome casts doubts on central banks' ability to fully implement an IT strategy in emerging economies. The question that arises is as to whether interest rate is the right tool to handle for these central banks.

Target achievement

I used two alternative definitions of price dynamics: inflation and inflation exceeding the central bank's target. Inflation is measured as the year-on-year change in the Consumer Price Index (quarterly data from IMF's International Financial Statistic). The inflation rate gives us good information about the economic momentum of a country, and about how much it has been impacted by the global inflation shock. However, the goal of an inflation-targeting central bank is not to have zero inflation, but to keep inflation as close as possible to a given and announced target. Thus, monetary policy assessment is to be done on the basis of inflation deviation from that target. I call *excess inflation* the deviation of inflation from the targeted rate. Series of inflation targets have been collected form the national monetary authorities' websites. When the historical series were not provided in free access, I referred to the announced strategy published in monthly bulletin or others official publications. If ever a central bank does not announce a point target but a range target, I use the range's mean.

The estimation of equation 10 with X denoting inflation, provides a general picture of how large was the price surge: inflation increased by 1.5 percentage point in average in the economies that target inflation with a free float arrangement (Table 5 first column, $\alpha_0 = 1.46$, p-value$< 5\%$) , and it increased by about the same figures in economies with a managed exchange rate arrangement (α_1 is not significant). However, the magnitude of the inflation shock was quite less important in the second category of countries: α_1 had a negative value with a low p-value when corrected by the *pre*-period (in equation 11, $\alpha_1 = -1.26$, p-value $< 5\%$, Table 5, second column).

When estimating the same equations with X denoting excess inflation, the proper measure of target achievement, I get the same picture: the shock was smaller in hybrid inflation-targeting countries than in free floating countries: $\alpha_0 = 2.33$, p-value $< 1\%$ and $\alpha_1 = -1.86$, p-value $< 5\%$, Table 10, third column. This is true in level and while correcting for the previous excess inflation level (α_0 and α_1' low p-value in Table 10 fourth column).[14]

When estimating equation 11 for both inflation and excess inflation, I obtain a strongly negative coefficient α_2. Thus, the shock was painless in countries used to higher inflation, while it was stronger in countries where inflation was low or close to the target during the *pre*-period. The combination of a negative estimated α_1 and a negative estimated α_2 means

[14] Note that the better performance of HIT on excess inflation is also due to the higher target readjustment done by FIT between the two periods : in Table 5 the coefficient α_1 is bigger in column 1 than in column 3. HIT have modified their inflation targets by a smaller amount than FIT, which may have helped them to build credibility and keep inflation expectation close to the target.

Table 5: Impact of exchange rate control on prices

	Inflation π_t		Excess Inflation $\pi_t - \pi_t^\star$		Credibility $-(E_t[\pi_{t+1}] - \pi_t^\star)^2$	
	(eq 1)	(eq 2)	(eq 1)	(eq 2)	(eq 1)	(eq 2)
Constant (α_0)	1.46**	4.04***	2.33***	2.82***	-8.40***	-7.88***
	(.59)	(.74)	(.56)	(.42)	(2.15)	(2.47)
Dummy (α_1)	-1.19	-1.26*	-1.86**	-1.48**	6.19*	6.30*
	(1.00)	(.69)	(.95)	(.68)	(3.62)	(3.72)
X_{pre} (α_2)		-.48***		-.57***		.10
		(.11)		(.15)		(.20)
Groups	17	17	17	17	17	17
R-squared	.09	.6	.2	.62	.16	.18

Standard errors in brackets: *** p<0.01, ** p<0.05, * p<0.1

that the countries with more inflation before the crisis where the economies with the dummy variable $D = 1$, the managed float economies.

Finally, the estimation of equation 10 and equation 11 with X denoting inflation and excess inflation gives the following picture: the emerging inflation-targeting economies that have a perfectly floating exchange rate were in average economies with lower inflation and better target achievement during the period before the inflation shock. However, emerging inflation-targeting economies that have a managed exchange rate arrangement have been less impacted by the global price surge of 2007-2008: the inflation rate has remained more stable, and closer to the target.

Credibility

The credibility of monetary policy is always an important factor of its efficiency. This is particularly the case for inflation-targeting strategies, which purpose is to anchor the expectations, using communication and transparency. The credibility of a regime is usually measured by the proximity of private-sector inflation expectations to the inflation target. As underlined by Svensson (2009, page 27)): "The closer the expectations are to the target, the higher the degree of credibility". Also, it is worth noting that expectations below the target are not better than expectation above the target. Such expectations could, for instance, lead to higher structural unemployment (see Svensson (2013)) or (if extremely low) to deflation. This is why credibility was calculated as the negative square difference between central bank inflation target and expected inflation rate.

$$-C_{i,t} = \left(E_{i,t}[\pi_{i,t+j}] - \pi_{i,j}^\star\right)^2$$

The credibility index equals zero when expectations are exactly anchor to the target rate and it takes a large negative value when expectations are farer to the target. Private-sector inflation expectations are given by the WES survey[15]. The time horizon is the next year. There are several characteristics why the data set of the CESifo WES forecast poll is suitable for my analysis. First, the survey participants work with the private-sector in the respective country and hence, one can be confident they have accurate idea concerning the future economic development. Also using private-sector forecasts is also of advantage compared to the projections of international institutions like the IMF or OECD : the latter might have an incentive to report strategic forecasts consistent with their macroeconomic policy, as shown by Dreher et al. (2008), while the private-sector should have an incentive to provide an accurate forecast rather than a strategic forecast, as shown by Batchelor (2001). Second, the forecasts are not revised. Hence, they are not exposed to the real-time data critic. Orphanides (2001) has shown how important it is to distinguish between real-time and revised data to correctly assess the information set on which the central bank sets its interest rate. Lastly, the data set allows me to compare the results among all countries since it does not suffer from problems resulting from different reporting standards.

The estimation of both equations 10 and 11 gave significant results. Free floaters credibility dropped by -8.40 with the shock, while hybrid inflation targeters credibility fell, on average, by 6.19 pp less than free floaters credibility did (estimation of α_0 and α_1 in equation 10, p-value$<$ 1% and 10% respectively, fifth column of Table 5). This difference in the fall is statistically significant with and without correcting for the credibility before the shock (estimation of α_1 in equations 10 and 11, p-value$<$ 10%, fifth and sixth column of Table 5).

Our results seem to indicate that exchange rate control contributed to limiting the extent to which the inflation rate, excess inflation, and credibility worsened. This result suggests that Hybrid inflation targeters had a better monetary anchor than free floating inflation targeters.

Efficiency curve

The efficiency of a monetary policy is generally evaluated by using the Taylor curve (after Taylor (1979), see Svensson (2009)), which represents the ability of a central bank to control inflation without creating too much production volatility and vice-versa. Results for the volatility of inflation, excess inflation and credibility are given in Table 6. Results about real GDP growth and volatility are shown in Table 7. Real GDP growth rate is calculated on year-on-year basis. Volatility is calculated as the squared deviation from 6 quarters moving average.

[15]The CESifo World Economic Survey is a publication by the Center for Economic Studies and Ifo Institute. It "assesses worldwide economic trends by polling transnational as well as national organisations worldwide on current economic developments in their respective countries. Its results offer a rapid, up-to-date assessment of the economic situation prevailing around the world. In January 2013, 1,169 economic experts in 124 countries were polled."

Table 6: Impact of exchange rate control on price volatility

	Inflation Vol. σ_{π_t}		Excess Infl. Vol. $\sigma_{\pi_t-\pi_t^\star}$		Credibility Vol. $\sigma_{(E_t[\pi_{t+1}]-\pi_t^\star)^2}$	
	(eq 1)	(eq 2)	(eq 1)	(eq 2)	(eq 1)	(eq 2)
Constant (α_0)	.22	1.92*	.22	1.86*	128.40**	131.92*
	(.98)	(1.15)	(.91)	(1.08)	(63.80)	(69.86)
Dummy (α_1)	2.43	1.24	2.21	1.10	15.30	12.19
	(1.66)	(1.56)	(1.53)	(1.44)	(107.39)	(112.89)
X_{pre} (α_2)		-.49**		-.44**		-.03
		(.22)		(.19)		(.18)
Groups	17	17	17	17	17	17
R-squared	.13	.36	.12	.36	.001	.003

Standard errors in brackets: *** p<0.01, ** p<0.05, * p<0.1

For any of these variables, when estimating both equation 10 and 11, the estimated α_1 coefficient, associated to the regime dummy, is not statistically significant. The shock did not imply different patterns for volatility in Flexible IT and Hybrid IT.

Inflation and excess inflation volatilities have increased significantly with the shock: $\alpha_0 = 1.92$ and 1.86 respectively, with p-value$<$ 10% (Table 6) when correcting for the volatility before the shock. The significant and negative value associated to α_2 means that inflation and excess inflation has increased the most in these countries where it was lower before the shock ($\alpha_2 = -.49$ and $-.44$ respectively, with p-value$<$ 5% , second and third column Table 6). Results for credibility's standard deviation are similar, without significance of the *pre*-period variable: credibility was more volatile after the shock than before for any given value during the *pre*-period. The estimated value of α_0 when X is denoting real GDP growth is strongly negative. Interestingly, real GDP growth rate has fallen by around the amount than inflation rate has jumped : almost 1.5 pp ($\alpha_0 = -1.44$ for GDP and -1.46 for inflation, both with p-value$<$ 5% , in Table 7). The average growth was lower after than before the shock, for the two types of countries (α_1 is not statistically different from 0). The years following the shock are also associated to a higher volatility of real GDP growth ($\alpha_0 = 0.55$, with p-value$<$ 10% when correcting for *pre*-period level, in Table 7) .

Finally, these results show no support for a movement *along* the Taylor curve: both inflation and GDP volatility have increase after the shock. Rather than a move along the Taylor curve, this implies a jump from a given curve to a second one, farer away from the zero point. In other words, the *post*-period Taylor curve represents a less efficient monetary policy than the *pre*-period curve. This fall in efficiency was expected because the *post*-period was the shock's period. However, results about the Taylor curve and those about the Taylor principle, seems to indicated that the central banks did not choose to control inflation at the expense of GDP

Table 7: Impact of exchange rate control on production and interest rate setting

	GDP growth g_t		vol(GDP growth) σ_{g_t}		Interest Rate R_t	
	(eq 1)	(eq 2)	(eq 1)	(eq 2)	(eq 1)	(eq 2)
Constant (α_0)	-1.44**	-.51	.08	.55*	-1.36***	-1.07
	(.65)	(.91)	(.47)	(.31)	(.50)	(.69)
Dummy (α_1)	.94	1.48	-.39	-.08	.97	.86
	(1.09)	(1.12)	(.80)	(.49)	(.90)	(.94)
X_{pre} (α_2)		-.16		-.36***		-.07
		(.11)		(.07)		(.11)
Groups	17	17	17	17	16	16
R-squared	.05	.17	.02	.65	.08	.1

Standard errors in brackets: *** p<0.01, ** p<0.05, * p<0.1

growth. Most importantly, this pattern is shared by both the free floaters and the hybrid inflation targeters.

6 Conclusion

My approach is based on the exchange rate regimes classification method developed by **?**: as them, my classification is based on three variables (the nominal exchange rate volatility, the interventions in the foreign exchange market , volatility of nominal exchange rate changes) and a clustering method. However, the patitioning algorithm I propose is more accurate since 1) it gives a criterion to define the number of policy groups, 2) the clusters shape is flexible (while it was constraint in LYS case) insuring that in my clusters observations really are similar. 3) I also propose a routine to insure the result stability and robustness; and 4) I introduce a control sample system to bridge clusters and monetary policy.

Over the 18 emerging economies that have adopted inflation targeting, I find clear evidence that 10 of them have an exchange rate as flexible as the developed IT economies, 4 have a managed float arrangement while the remaining 4 have an exchange rate system as rigid as the standard peg currencies. My results show strong support to distinguish two different monetary regimes under inflation targeting: Flexible IT when the monetary authorities handle only one tool, the interest rate, and Hybrid IT when the monetary authorities add foreign exchange interventions to their tool-box.

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A Methodological Appendix: From k-means to Gaussian mixture

I this Methodological Appendix, I show how the Gaussian mixture that I use differ from the K-means alogorithm used by **?**. Indeed, LYS' k-means is similar to the Gaussian, but it supposed two limitations: the covariance matrix is constraint, and the probability to belong to a group is not computed. Therefore, the constraint on the covariance matrix gives to their clusters a circular shape, and all clusters are being of similar size. Also, in their approach, the probability for an observation to belong to a group is not computed. An observation either belong to a group or not. Whereas in my approach the clusters' shape is flexible, and a precise probability to belong to a group is computed. All in all, the Gaussian mixture approach seems more flexible and robust than those with k-means.

K-means cluster analysis

The K-means algorithm is a clustering method, which is used to divide a given set of objects into groups, called clusters, such that objects within a group tend to be more similar, or closed, to one another as compare to objects belonging to different goups. As simply said by Wu & Kumar (2010, page 21) "clustering algorithms place similar points in the same cluster while placing dissimilar points in different clusters". It was independently discovered by Steinhaus (1956) and Lloyd (1982) (Unpublished Bell Lab. Note of 1957, see Jain (2010) for a wider historical perspective).

Let $X = x_1, x_2, ..., x_M$ be a set of M d-dimensional points, to be clustered into a set of K clusters, denoted by $C = c_1, c_2, ..., c_K$. K-means algorithm finds a partition such that the within-cluster sum of squares is minimized. Let μ_k be the mean of cluster c_k. The default measure of closeness is the Euclidean distance. Thus, the squared error between μ_k and the points in cluster c_k is given by:

$$J(c_K) = \sum_{x_m \in c_k} ||x_m - \mu_k||^2 \tag{12}$$

The goal of K-means is to minimize the within-cluster sum of squares over all K clusters:

$$arg\ \ min \sum_{k=1}^{K} \sum_{x_m \in c_k} ||x_m - \mu_k||^2 \tag{13}$$

The cluster means, μ_k with $k = 1, 2..., K$, also called cluster centroids, allow to represents each of the k clusters by a single point in $\mathcal{R}^d$ As described by Levy-Yeyati & Sturzenegger (2005, page 8), "K cases in the data file, where K is the number of clusters requested, are selected as temporary centers. As subsequent cases are processed, a case replaces a center if the smallest distance to a center is greater than the distance between the two closest centers. The center that is closer to the case is replaced. A case also replaces a center if the smallest distance from the case to a center is larger than the smallest distance between the center and all other centers. Again, it replaces the center closest to it. The procedure continues until all cases are classified."

The K-means algorithm clusters in an iterative fashion, alternating between reassigning the cluster of all points, and updating the empirical mean of each cluster. The main steps of K-means algorithm are as follows (see Jain & Dubes 1988)

- Select an initial partition with K clusters,
- Assignment step: generate a new partition by assigning each observation to the cluster with the closest mean

$$C_k^{(t)} = \{x_m : ||x_m - \mu_k|| \leq ||x_m - \mu_{k*}^{(t)}|| \tag{14}$$

  where (t) represents the iterative step, for all $k^* = 1, ..., K$

- Update step: Calculate the new means to be the centroid of the observations in the cluster.

$$\mu_k^{(t+1)} = \frac{1}{c_k^{(t)}} \sum_{x_m \in c_k^{(t)}} x_m \tag{15}$$

- Repeat assignment and update steps until cluster membership stabilizes.

The algorithm converges when the assignments, and hence the centroids values, no longer change. One can show that the objective function defined in equation (13) will decrease whenever there is a change in the assignment or the relocation steps, and convergence is guaranteed in a finite number of iterations.

From k-means to Gaussian mixture

The k-means is similar to the Gaussian, but it supposed two limitations: the covariance matrix is constraint and the probability to belong to a group is bi-modal.

Following Vishwanathan (2011), let assume that the covariances of the mixture components are given by $Sigma_m = \epsilon Id$, where $\epsilon > 0$ and Id denotes the identity matrix. In this case the univariate Gaussian distribution given by equation (1) reduces to

$$\mathcal{N}(x|\mu, \epsilon I) = \frac{1}{\sqrt{2\pi\epsilon}} exp\left(-\frac{1}{2\epsilon}||x - \mu||^2\right) \tag{16}$$

Then, equation (6) can be written as :

$$\pi_{m,k} = \frac{\pi_k \; exp\left(-\frac{1}{2\epsilon}||x_m - \mu_k||^2\right)}{\sum_{k'} \pi_{k'} \; exp\left(-\frac{1}{2\epsilon}||x_m - \mu_{k'}||^2\right)} \tag{17}$$

Let $\mu_{k'}$ denotes the μ that minimizes $||x_m - \mu||$ (that is $\mu_{k'}$ is the closest μ to x_m. If one assume $\epsilon \rightarrow 0$ then $\pi_{m,k} \rightarrow 0$ for all k except for k', and $\pi_{m,k'} \rightarrow 1$ for j' .

Let $r_{m,k}$ be defined as:

$$\pi_{m,k} = \begin{cases} 1 & \text{if} k = argmin_{k'}||x_m - \mu_{k'}||^2 \\ 0 & \text{otherwise} \end{cases}$$

Then, we can rewrite equation (12) which minimizes within-cluster sum of square over all cluster k, in term of Gaussian mixture model's equation (4), as:

$$J(\pi, \mu) = \sum_{m=1}^{m} \sum_{k=1}^{K} \pi_{m,k}||x_m - \mu k||^2 \tag{18}$$

This is equivalent to add a binary parameter in the minimizing within-cluster sum of squares, as defined by equation (12) and (13) and thus, this is equivalent to the K-means algorithm .

To resume, I have established the connection between the Gaussian mixture model and the k-means algorithm. To do so, I have to assume that the covariance matrice of the mixture components was constrained, with equal variance among the groups. This is equivalent to the model EII in Table 3.2. Therefore, I can consider that the k-means problem as defined by Levy-Yeyati & Sturzenegger (2005) for grouping monetary regimes, is a particular case of the more general gaussian mixture problem I handle here. Futhermore classifying exchange rate regimes using the Gaussian mixture model approach, gives, first, a criterium to determine the number of clusters, and then, the best fit among various model. In particular it allows my cluster to be ellipsoidal and not constraint to circles like in LYS.

B Appendix: Classification

B.1 Data set

The currency of reference for each country is used as numeraire. It is either the US dollar or the Euro. The list of inflation targeting countries consists of emerging economies (Status = emerging) and developed economies (Status = developed). Developed economies are used in the control sample as indicator of flexible exchange rates policies while we assess emerging economies exchange rate arrangement. Fix exchange rate countries are the counterpart of developed IT countries: they are used in the control sample as indicator of fix exchange rates policies.

Table B.8: Inflation targeting countries

Country	IT adoption	Status	Numeraire
Albania	2009	emerging	EUR
Armenia	2006	emerging	EUR
Australia	1993	developed	USD
Brazil	1999	emerging	USD
Canada	1991	developed	USD
Chile	1999	emerging	USD
Colombia	1999	emerging	USD
Czech Rep.	1998	emerging	EUR
Ghana	2007	emerging	USD
Guatemala	2005	emerging	USD
Hungary	2001	emerging	EUR
Iceland	2001	developed	EUR
Indonesia	2005	emerging	USD
Israel	1997	developed	USD
Korea	2001	developed	USD
Mexico	2001	emerging	USD
New Zealand	1990	developed	USD
Norway	2001	developed	EUR
Peru	2002	emerging	USD
Philippines	2002	emerging	USD
Poland	1998	emerging	EUR
Romania	2005	emerging	EUR
Serbia	2006	emerging	EUR
South Africa	2000	emerging	USD
Sweden	1993	developed	EUR
Thailand	2000	emerging	USD
Turkey	2006	emerging	USD
United Kingdom	1992	developed	EUR

Table B.9: Fix exchange rate countries

Country	Numeraire	Country	Numeraire
Aruba	USD	Lesotho	USD
Bahamas, The	USD	Lithuania	EUR
Bahrain, Kingdom of	USD	Macedonia, FYR	EUR
Barbados	USD	Malaysia	USD
Belize	USD	Maldives	USD
Bhutan	USD	Namibia	USD
Bolivia	USD	Nepal	USD
Bosnia & Herz.	EUR	Netherlands Antilles	USD
Brunei Dar.	USD	Oman	USD
Bulgaria	EUR	Qatar	USD
Cape Verde	USD	Saudi Arabia	USD
China	USD	Seychelles	USD
Comoros	USD	Slovenia	EUR
Croatia	EUR	Suriname	USD
Djibouti	USD	Swaziland	USD
Eritrea	USD	Syrian Arab Rep.	USD
Estonia	EUR	Tanzania	USD
Guinea	USD	Turkmenistan	USD
Hong Kong	USD	Ukraine	USD
Iraq	USD	United Arab Emirates	USD
Jordan	USD	Venezuela, Rep.	USD
Kazakhstan	USD	WAEMU	EUR
Kuwait	USD	Zimbabwe	USD
Lebanon	USD		

B.2 Variables computation.

The three variables are computed as follows:

- Exchange rate volatility

$$\sigma e_t = \sum_{t=1}^{T} \frac{|log(e_t) - log(e_{t-1})|}{T}$$

With e the price of a reference currency in terms of local currency, and t takes values during a calendar year. The nominal exchange rate is given in IMF's International Financial Statistics. The reference currency for each country is presented in Table B.1.

- Volatility of exchange rate changes

$$\sigma_{\Delta et} = std\left(|log(e_t) - log(e_{t-1})|\right)$$

- Volatility of reserves

$$\sigma r_t = \sum_{t=1}^{T} |\frac{log(Res_t) - log(Res_{t-1})}{log(MB_t) - log(MB_{t-1})}|/T$$

Where Res is defined as $Res_t = FA_t - FL_t - Gov_t$, with MB is the monetary base, FA are the foreign assets, FB are the foreign liabilities and Gov the central government deposits. Following Levy-Yeyati & Sturzenegger (2005, page 1608) we use IMF's International Financial Statistics line 14, 11, 16c and 16d respectively. All variables are expressed in US dollars.

B.3 Classification scheme.

The exact procedure to label the clusters is the following. The number of components, or number of Gaussians, is given by the maximisation of the Bayesian information criterion (BIC). We present two cases :

In case BIC indicates three Gaussians, a cluster is simply defined as one Gaussian.

- The clusters with the smallest average nominal exchange rate, $min\ \bar{\sigma e}$, is *de facto* fix.
- Among the two remaining clusters, the one with the majority of floating indicators countries is *de facto* floating.
- For the last cluster:
  - If the average reserves volatility , $min\ \bar{\sigma r}$, is higher than the average reserves volatility of the *de facto* floating cluster, this cluster is *de facto* intermediate.
  - If the average nominal exchange rate volatility, $min\ \bar{\sigma e}$, is higher than the average nominal exchange rate volatility of the *de facto* floating cluster, this cluster is *de facto* floating.
  - Else as I'm not able to label such a cluster, the procedure is rejected.

In case the BIC maximization indicates four Gaussians, two Gaussians are merged into one cluster, or one policy group:

- The Gaussian with the smallest average nominal exchange rate, $min\ \bar{\sigma e}$, is *de facto* fix.
- Among the three remaining Gaussians, the one with the smallest average reserves volatility, $min\ \bar{\sigma r}$, is *de facto* floating.
- Among the two remaining Gaussians, the one with the highest average reserves volatility, $min\ \bar{\sigma r}$, is *de facto* managed floating.
- The last group of observation is labelled as *de facto* floating (fixed) if it contains a majority of floating (fixed) indicator countries.

If the optimal number of Gaussian is higher than 4, then the procedure is rejected.

B.4 A robust classification procedure.

This section is dedicated to the presentation of two examples of random sampling classification, in order to assess the robustness and accuracy of the general classification procedure. Our final exchange arrangements classification results from the repetition of the classification algorithm presented in Section B.3 page 41. This algorithm is run thousand of times, on different samples of randomly picked up observations among the two control samples (the indicators countries). Finally, the regime associated to an observation (one country one year) is simply the one with the highest probability calculated over every random sampling repetition.

Table B.10: Gaussian Mixture Models Estimation: components statistics

	Fixed			Dirty Float			Free Floating		
				3 Gaussians					
	σe	$\sigma_{\Delta e}$	σr	σe	$\sigma_{\Delta e}$	σr	σe	$\sigma_{\Delta e}$	σr
min	0.00	0.00	0.00	0.06	0.01	0.03	0.03	0.02	0.01
mean	0.00	0.01	0.28	0.46	0.49	0.43	0.23	0.24	0.22
max	0.06	0.07	0.85	1.00	1.00	0.98	0.48	0.49	0.58
				4 Gaussians					
	σe	$\sigma_{\Delta e}$	σr	σe	$\sigma_{\Delta e}$	σr	σe	$\sigma_{\Delta e}$	σr
min	0.00	0.00	0.01	0.04	0.07	0.21	0.06	0.02	0.00
mean	0.00	0.01	0.25	0.26	0.27	0.56	0.30	0.32	0.17
max	0.04	0.05	0.95	0.72	0.80	0.97	1.00	1.00	0.58

Notation: Exchange Rate Volatility = σe ; Volatility of Exchange Rate Changes = $\sigma_{\Delta e}$; Volatility of Reserves = σr . Data are scaled to the unit interval, per variable, for each sample.

As said above, in case the BIC maximization indicates four Gaussians, two Gaussians are associated to one indicator countries policy. I do find this specification more appropriate. This specification first comes from the observation, on a graphical based, that two Gaussians are close and similar. This is also confirmed by plotting the uncertainty areas, where sections overlap. Also, to some extend, BIC maximisation may lead to four Gaussians due to outliers. Last the statistical properties of three clusters obtained by three or four (merged) Gaussians are similar and perfectly in line with those expected theoretically. The theoretical features are described in the literature review and summarized in Table 2 page 6, and the actual one, based on two random examples, are shown in Table B.4 page 42. Fix arrangements are associated to low exchange rate volatility, and to low volatility of exchange rate changes, and large volatility of reserves. Countries with flexible arrangements are associated with relatively low volatility of reserves and high volatility exchange rate. This is particularly true when looking at the center of each cluster (given by the mean). Last, the intermediate regime is perfectly matching with LYS's “dirty float" regime, given the relatively high values for the three variables.

Example: random sampling with 3 clusters: Figure B.4 page 44 has been plotted before the estimation of the Gaussian mixture model. It shows the histograms (on the left) and the kernel estimates of the density function (on the right) of each of the three classification variables. The estimation is done over the whole data-set. We clearly distinguish three modes.

Figure B.4 page 45 has been plotted after the estimation of the Gaussian mixture model. It shows the histograms and the kernel estimates of the density function of each Gaussian for each classification variables. Hence, the data set is no longer studied as a whole but as the sum of three sub-sets or as the results of the mixture of three Gaussians. Each sub-set correspond to the partition created by one Gaussian (that is why the number of sub-sets corresponds to the number of Gaussians). The histogram and kernel density of each sub-set is represented in a given color. Note that the clusters (sub-sets) kernel densities match very well with the modes that we distinguish on Figure B.4 page 44.

When estimating the Gaussian mixture model, the number of components, or in other words the number of Gaussians, is given by the maximisation of the BIC criterion. Figure B.3 page 46 shows the BIC value for different models, from 1 to 5 components. The different model are presented in Section **??** page 12. In the case represented here, the optimal model is VVV, which means that the volume, the shape and the orientation can vary from a cluster (or Gaussian) to the other. The optimal number of Gaussian is three. This was expected since we were able to distinguish three modes on Figure B.4 page 44.

Figure B.4 page 44 is a scatter plot of the three classification variables. Each of the three Gaussians resulting from the estimation of the Gaussian mixture model is represented by a color and shape. The blue dots form the cluster that will be labelled "Fix" exchange rate arrangement, while the green triangles compose the group of "Floating" exchange rate arrangement. The red cubes depict the "Intermediate" exchange rate policies, also called managed float. Note that, as described by Levy-Yeyati & Sturzenegger (2005), in Table 2 reproduced page 6 this group is characterised by large value of the three variables.

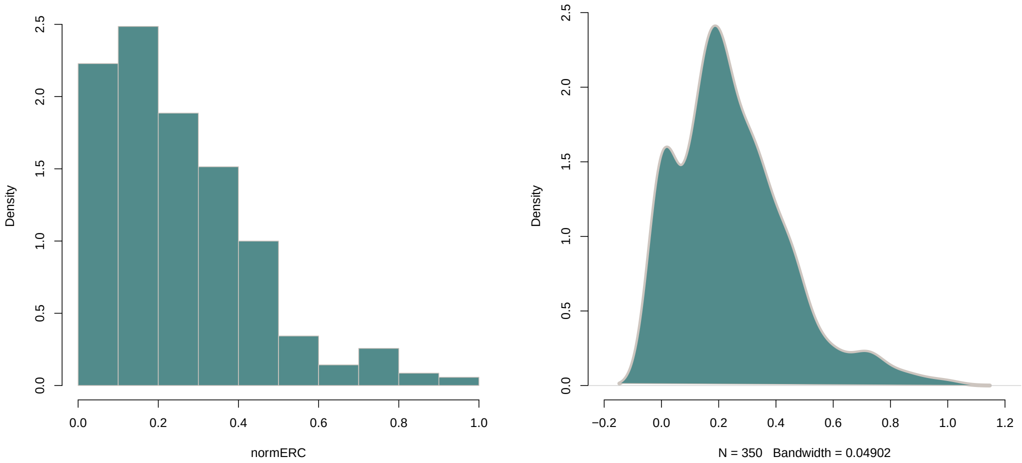
Figure B.4 page 48 is a scatter plot of the shape of the three clusters. Similar to Figure B.4 page 44 this representation is sometimes clearer.

On Figure B.4 page 49 the bolder and darker the observations, the higher the uncertainty is about the right Gaussian they belong to. On Figure B.4 page 50 a representation of the sample through the scatter plot of its estimated density.

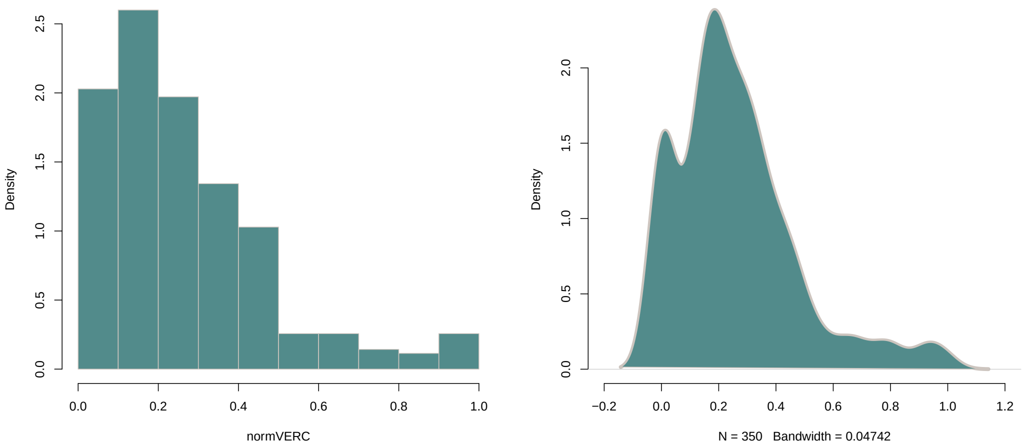
Example: random sampling with 4 clusters: The same figures are displays from page 51 to page 57 in the case of a sample (randomly composed) associated to 4 Gaussians.

Histogramm	Kernel density estimation

Exchange rate volatility σe



Volatility of Exchange Rate Changes $\sigma_{\Delta e}$



Reserves Volatility $\sigma_{\Delta e}$

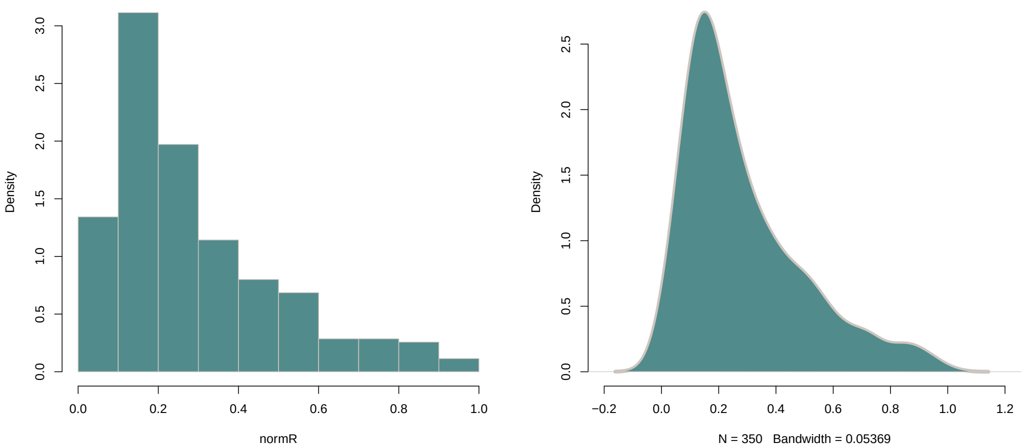
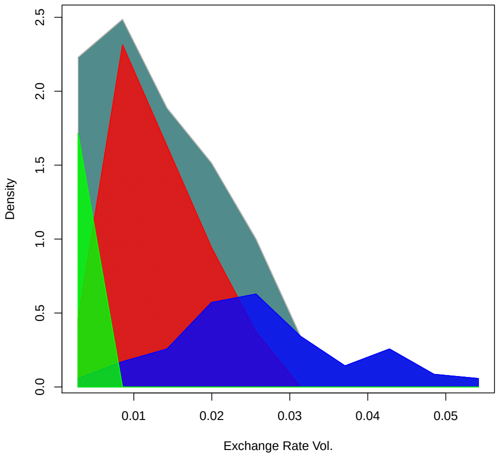
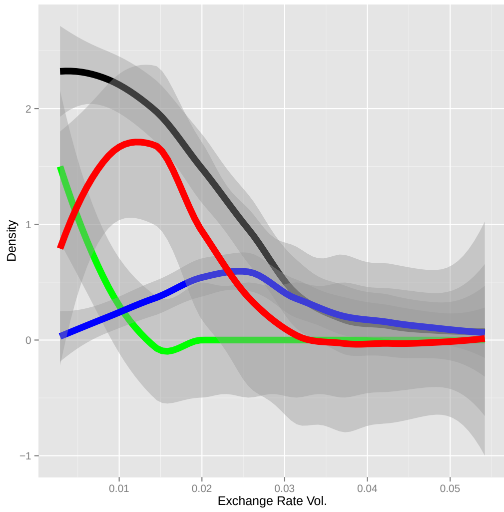


Figure B.1: Histogramm and Kernel estimation

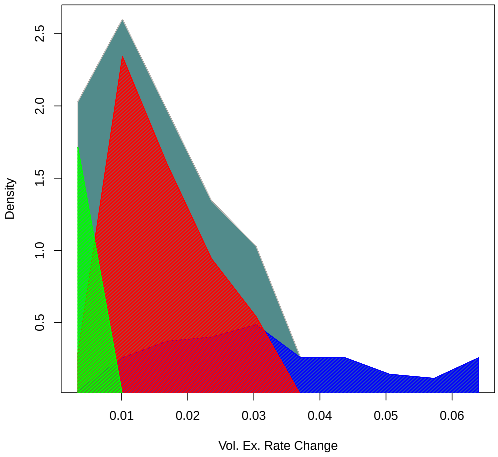
Histogramm decomposition	Adaptative kernel decomposition

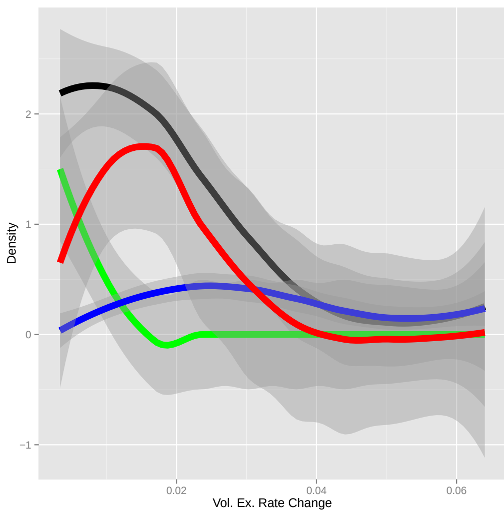
Exchange rate volatility σe



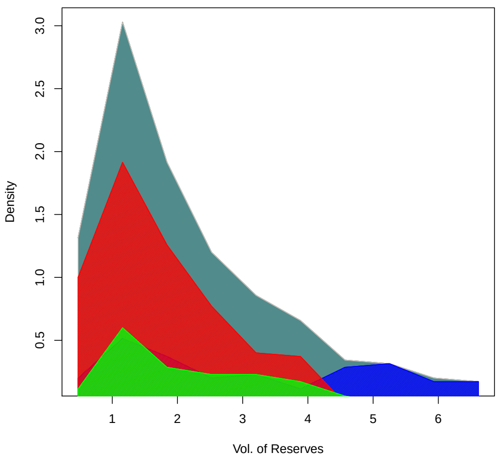


Volatility of Exchange Rate Changes $\sigma_{\Delta e}$





Reserves Volatility $\sigma_{\Delta e}$



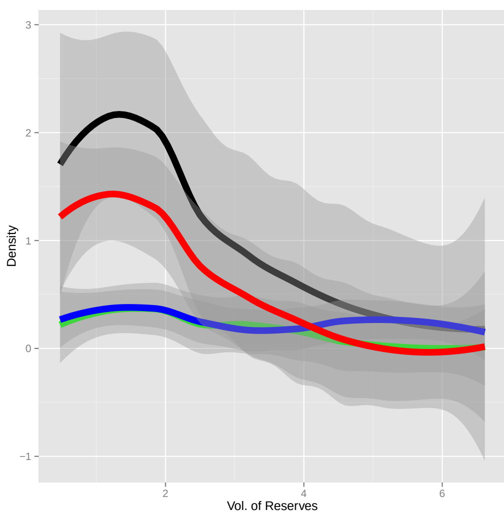


Figure B.2: Histogramm and adaptative Kernel decomposition

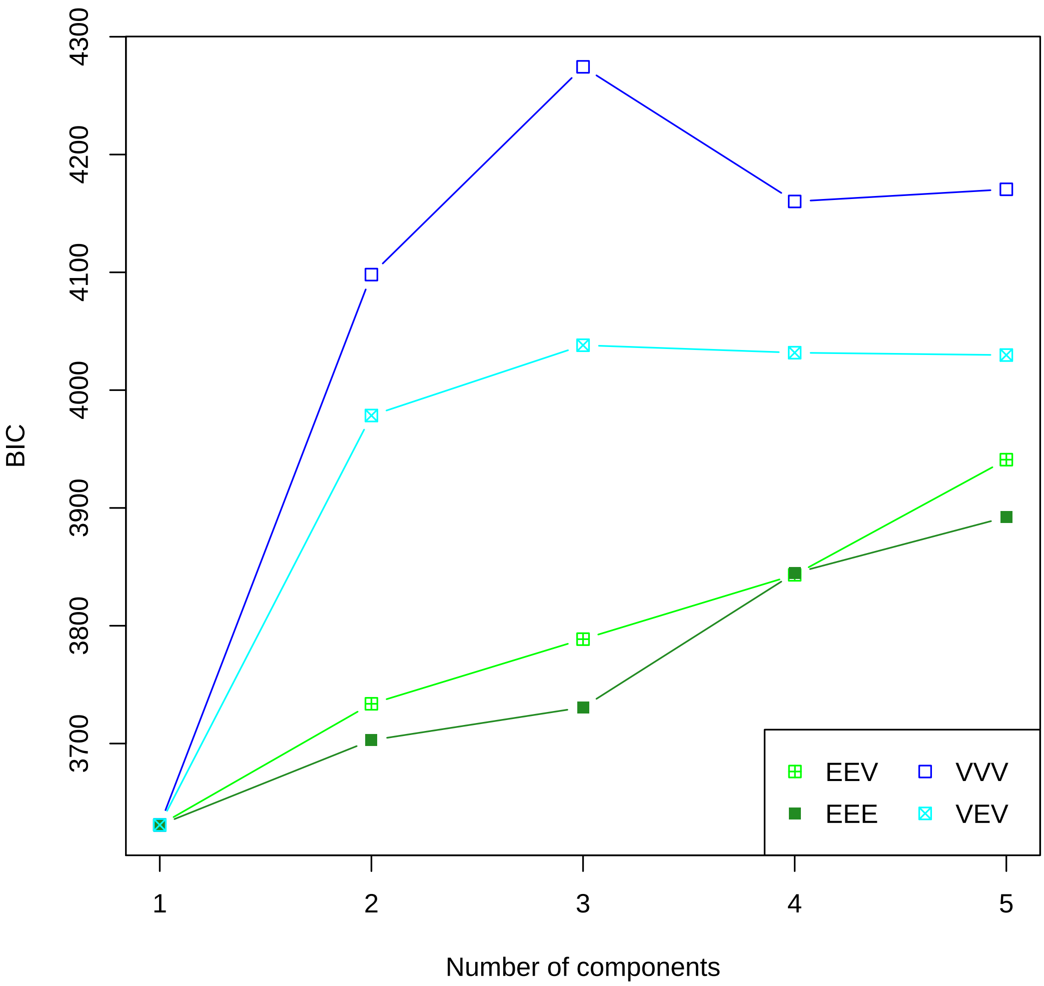


Figure B.3: BIC value for each model

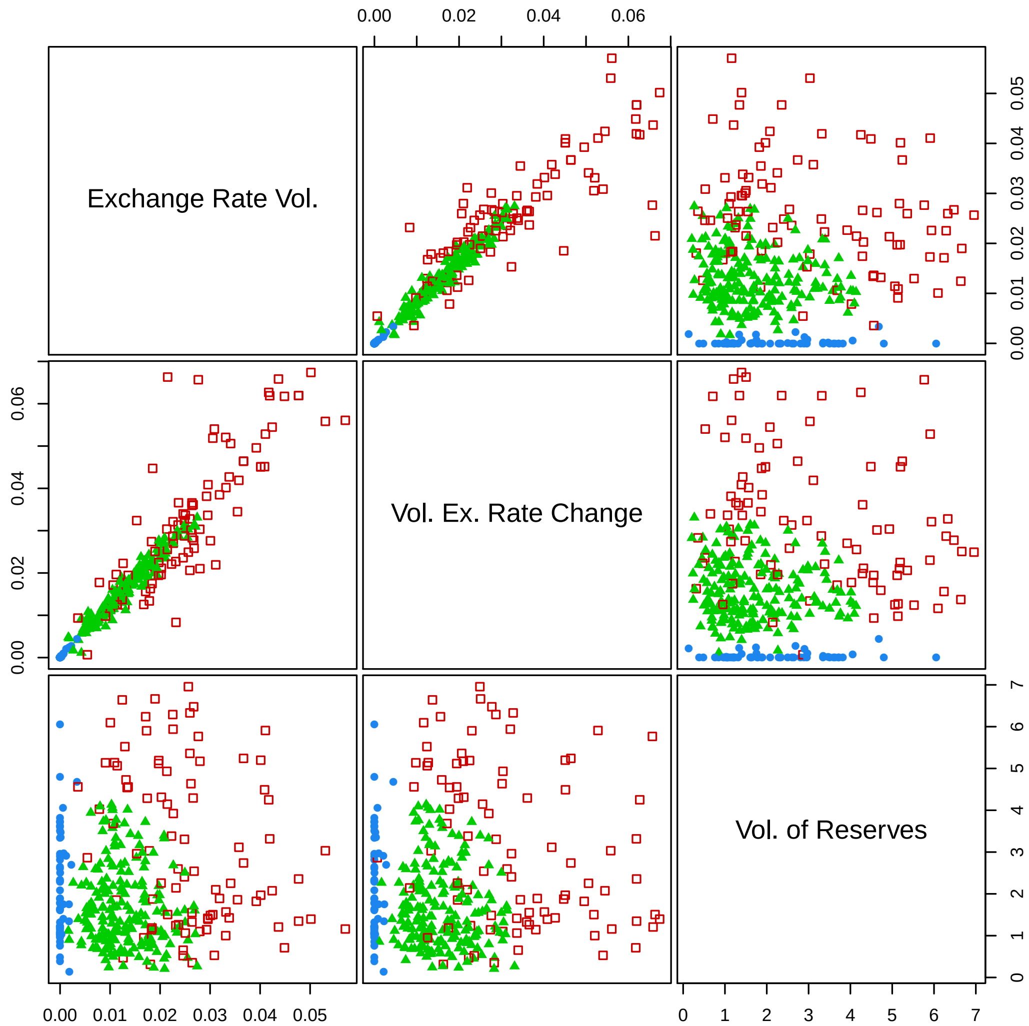


Figure B.4: Classification: 3 Gaussians

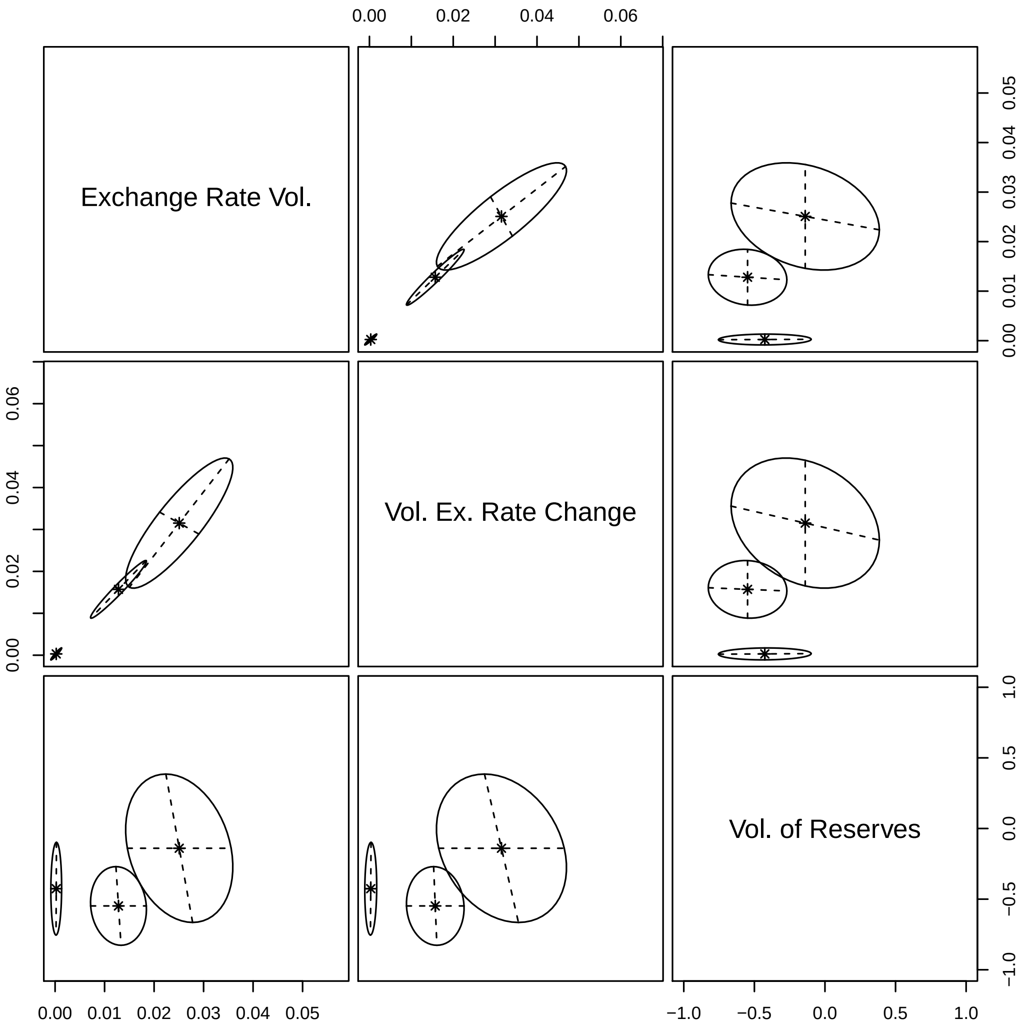


Figure B.5: Classification: shape of 3 Gaussians

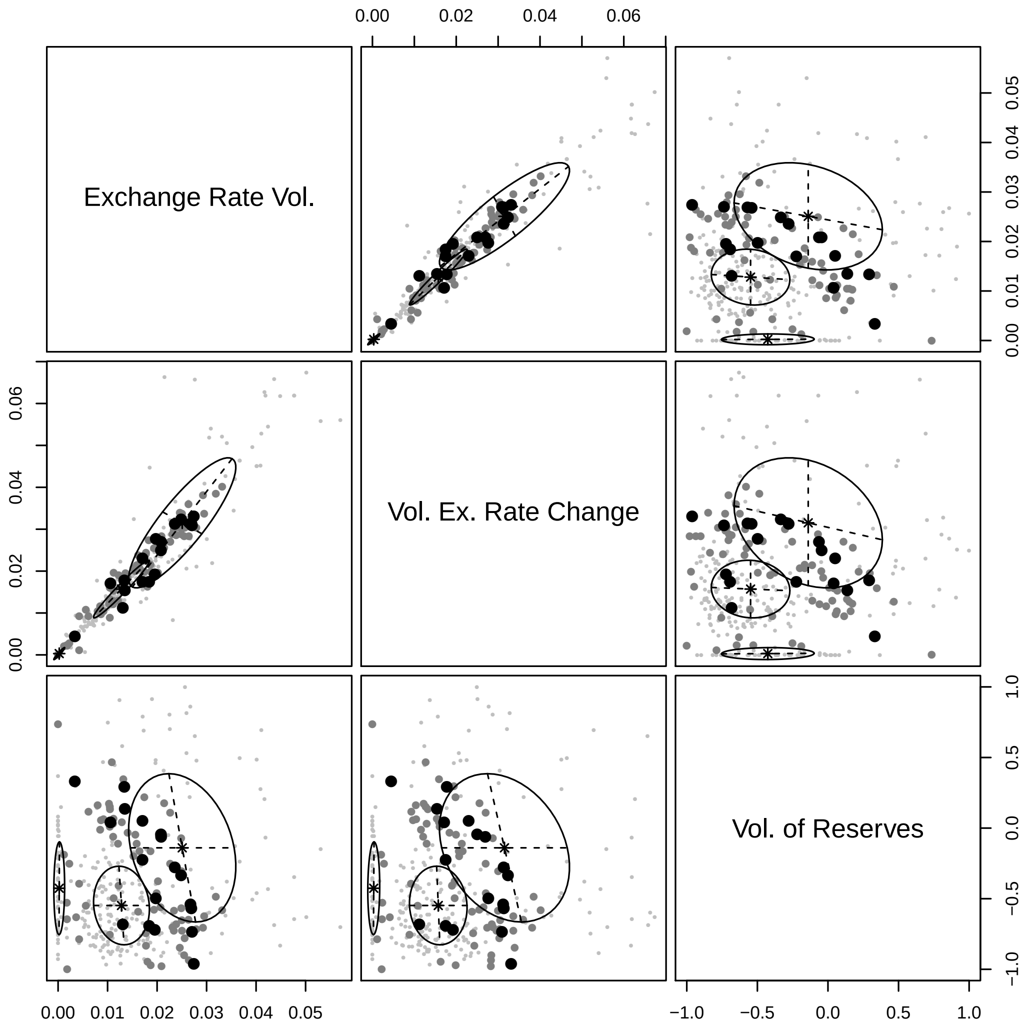


Figure B.6: Uncertainty

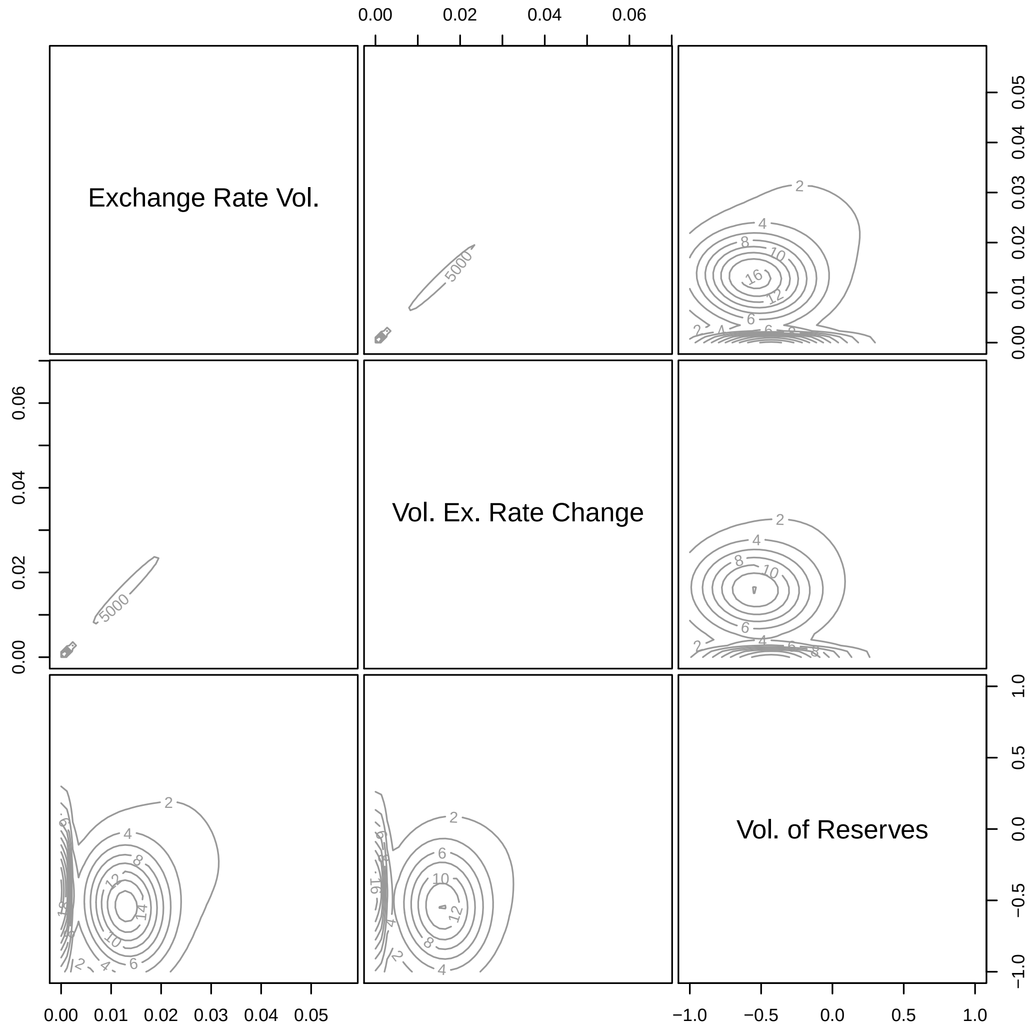
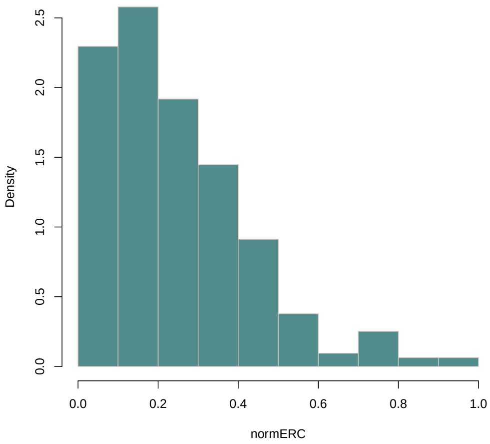
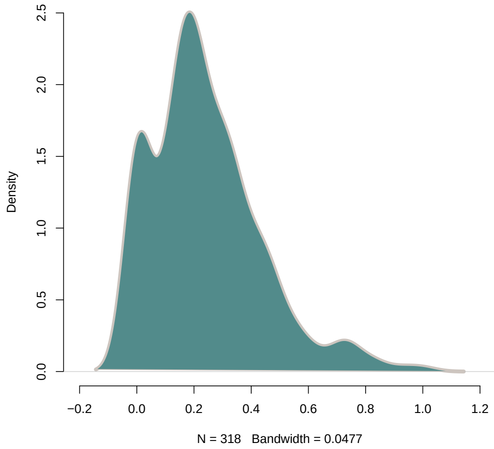


Figure B.7: Estimated density

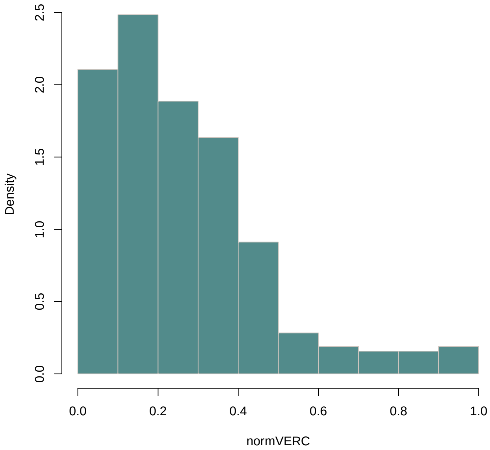
Histogramm	Kernel density estimation

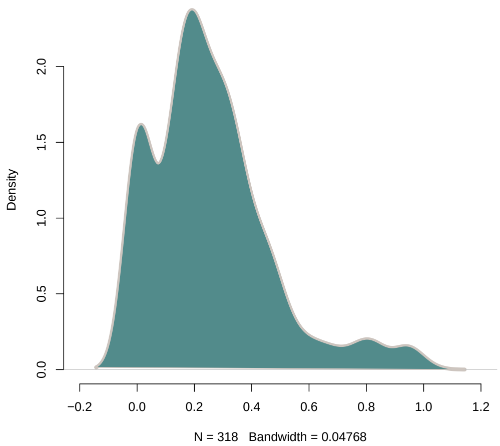
Exchange rate volatility σe



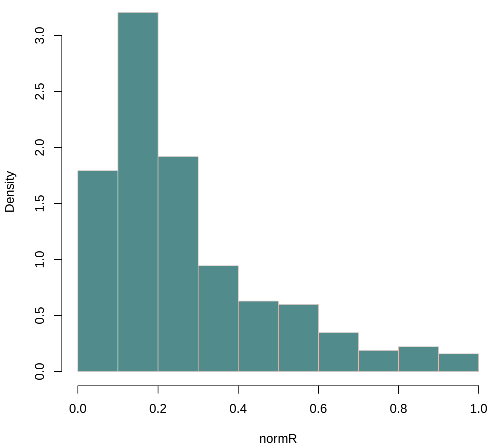


Volatility of Exchange Rate Changes $\sigma_{\Delta e}$





Reserves Volatility $\sigma_{\Delta e}$



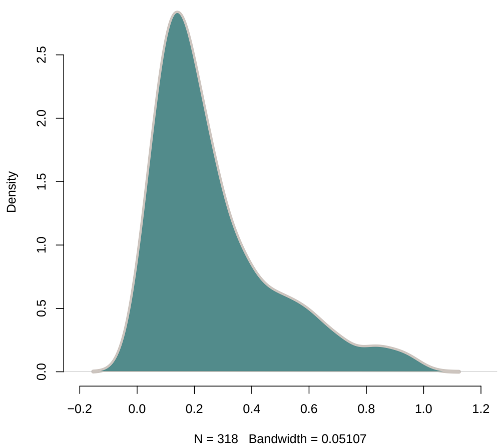
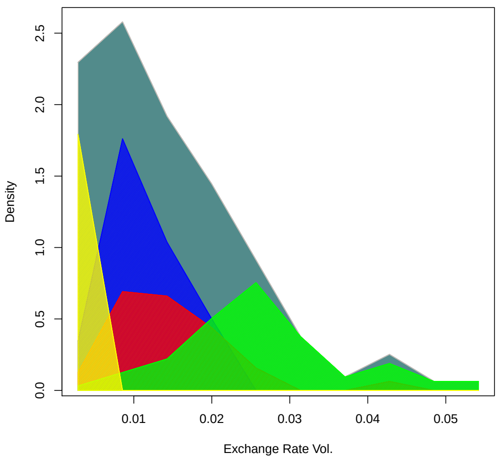
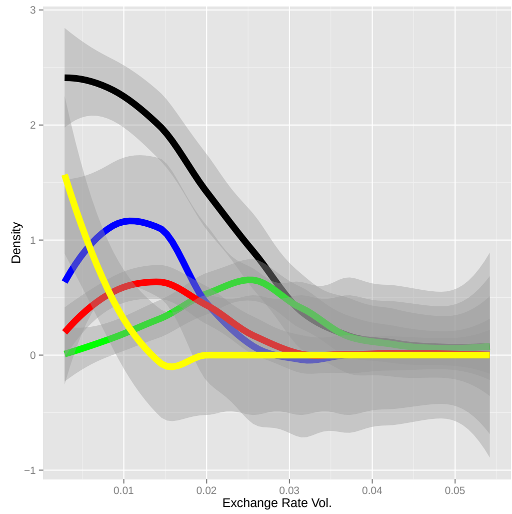


Figure B.8: Histogramm and Kernel estimation

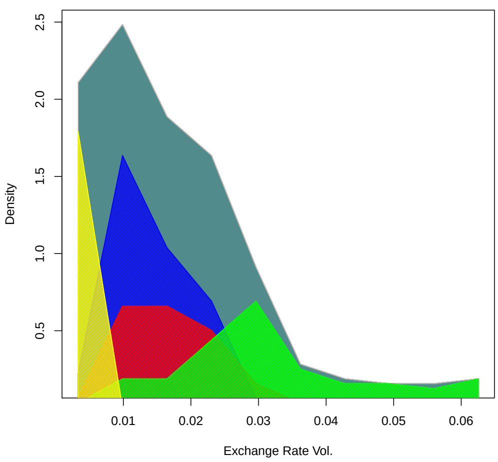
Histogramm decomposition	Adaptative kernel decomposition

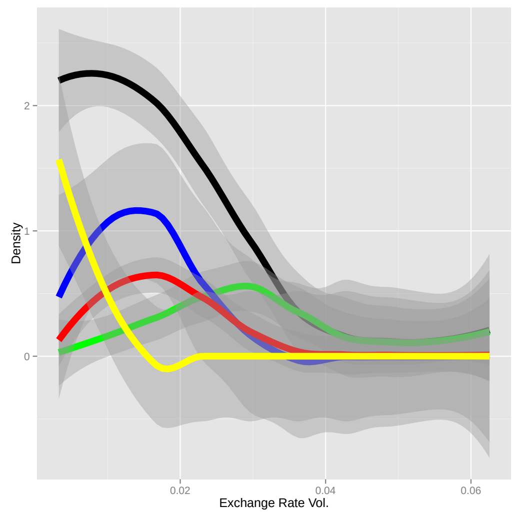
Exchange rate volatility σe



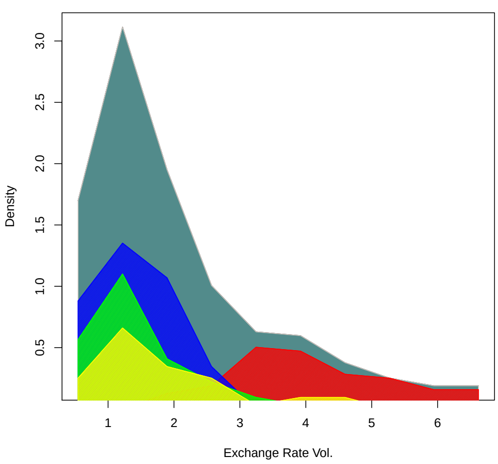


Volatility of Exchange Rate Changes $\sigma_{\Delta e}$





Reserves Volatility $\sigma_{\Delta e}$



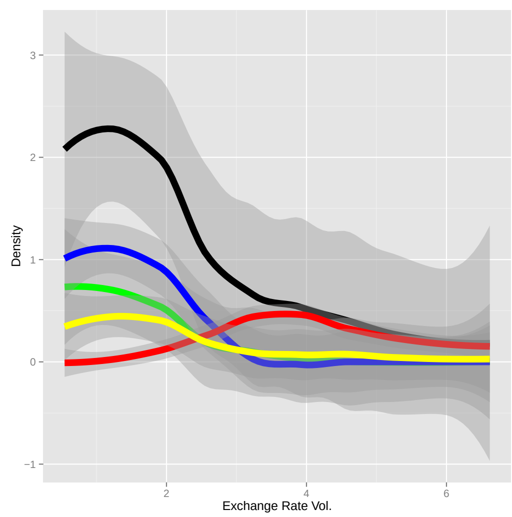


Figure B.9: Histogramm and adaptative Kernel decomposition

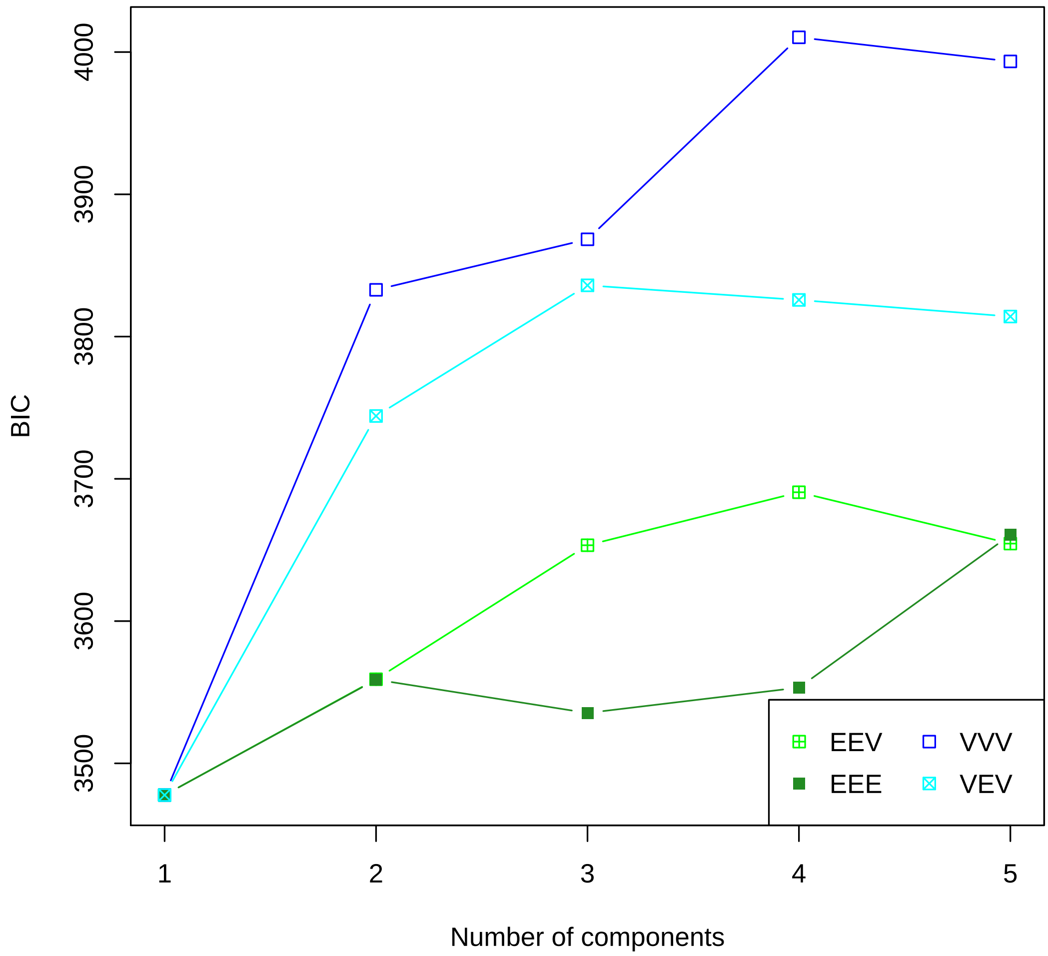


Figure B.10: BIC

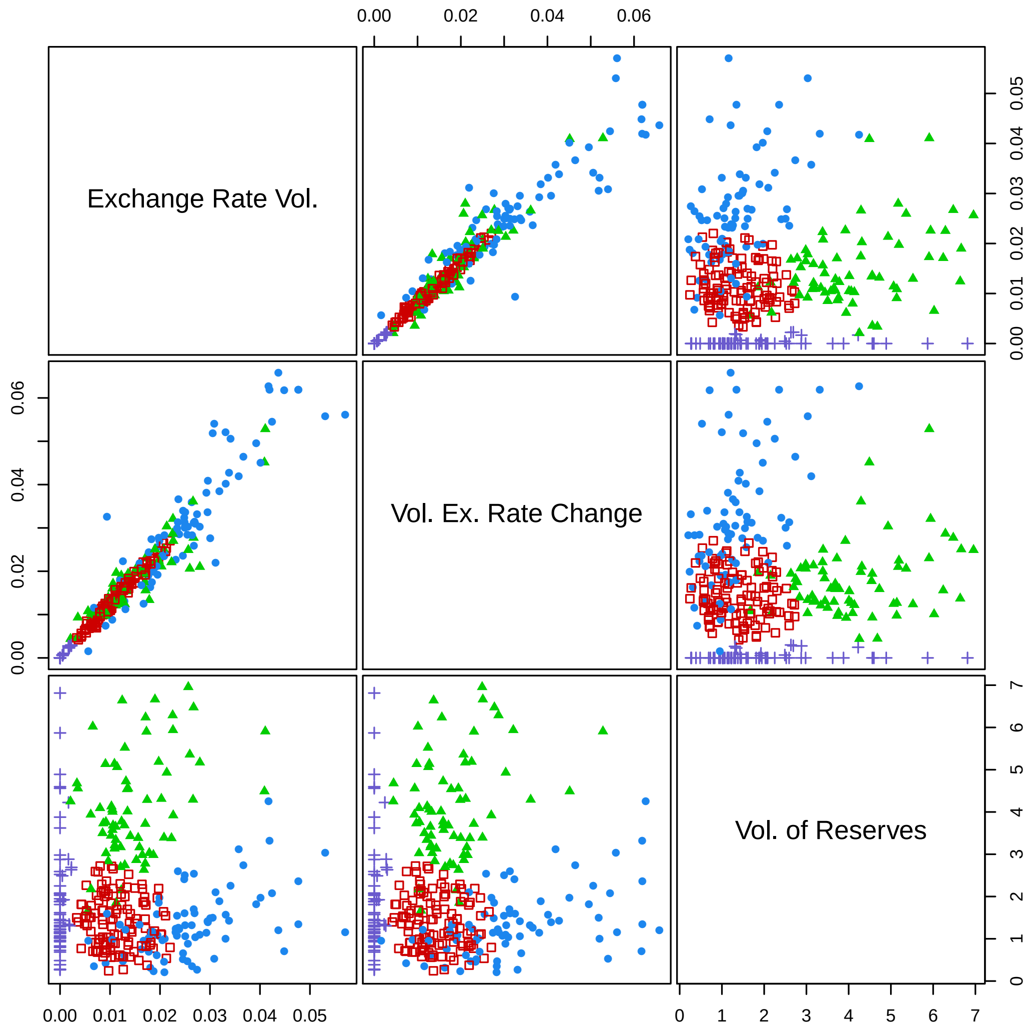


Figure B.11: Classification: 4 Gaussians

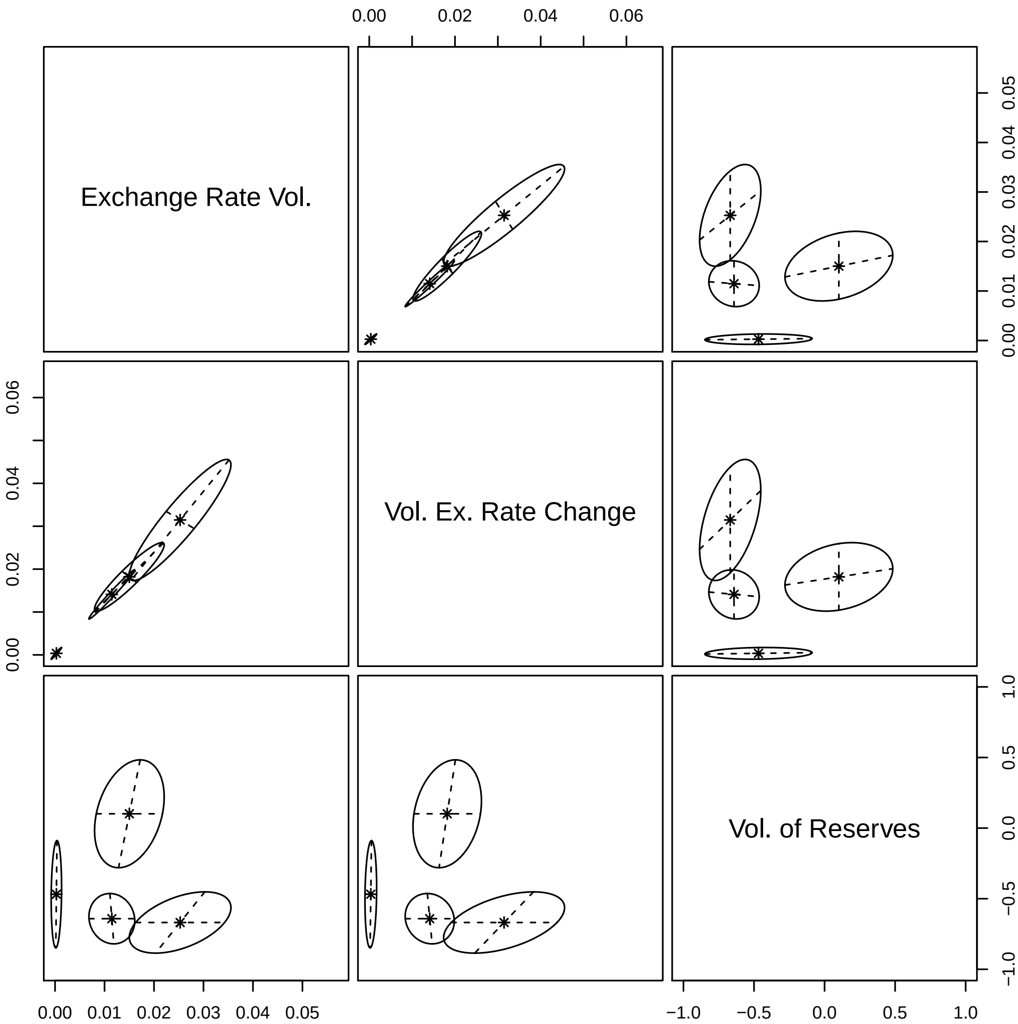


Figure B.12: Classification: shape of 4 Gaussians

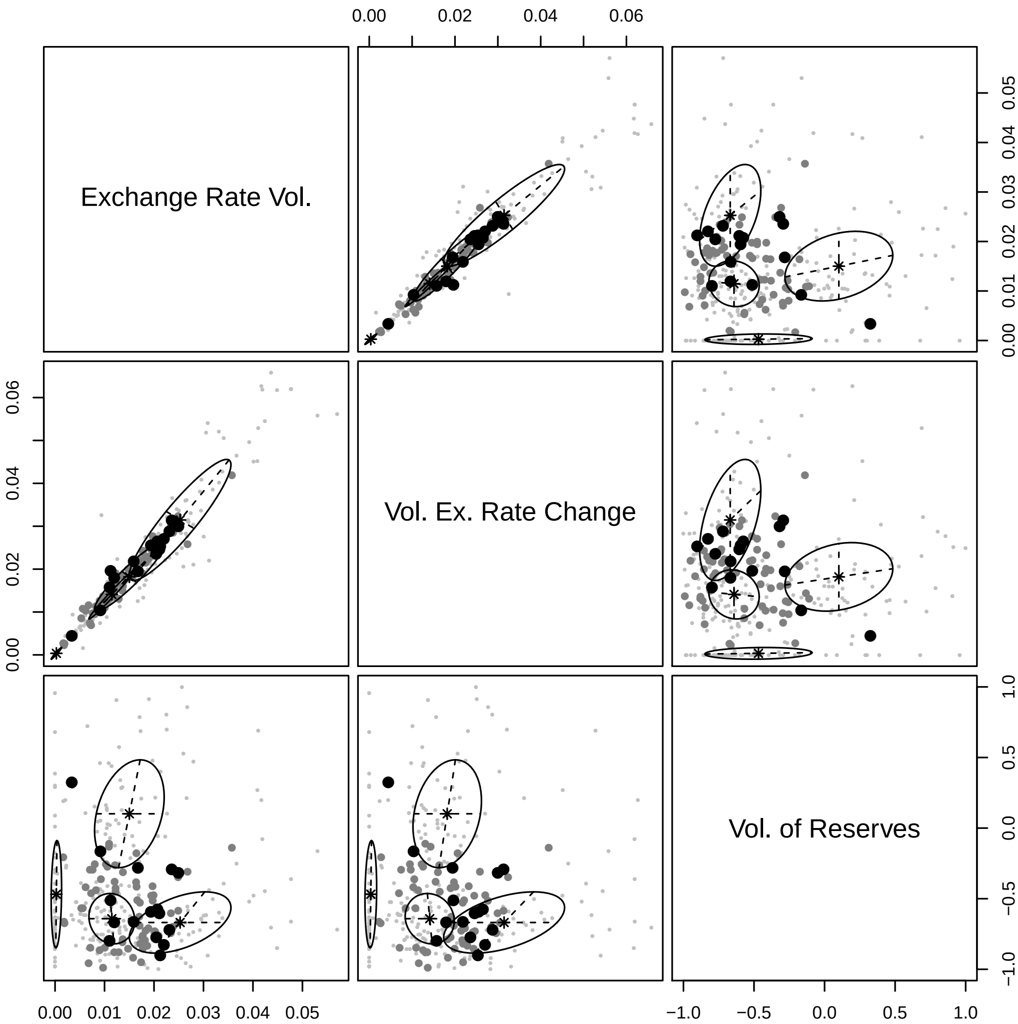


Figure B.13: Uncertainty

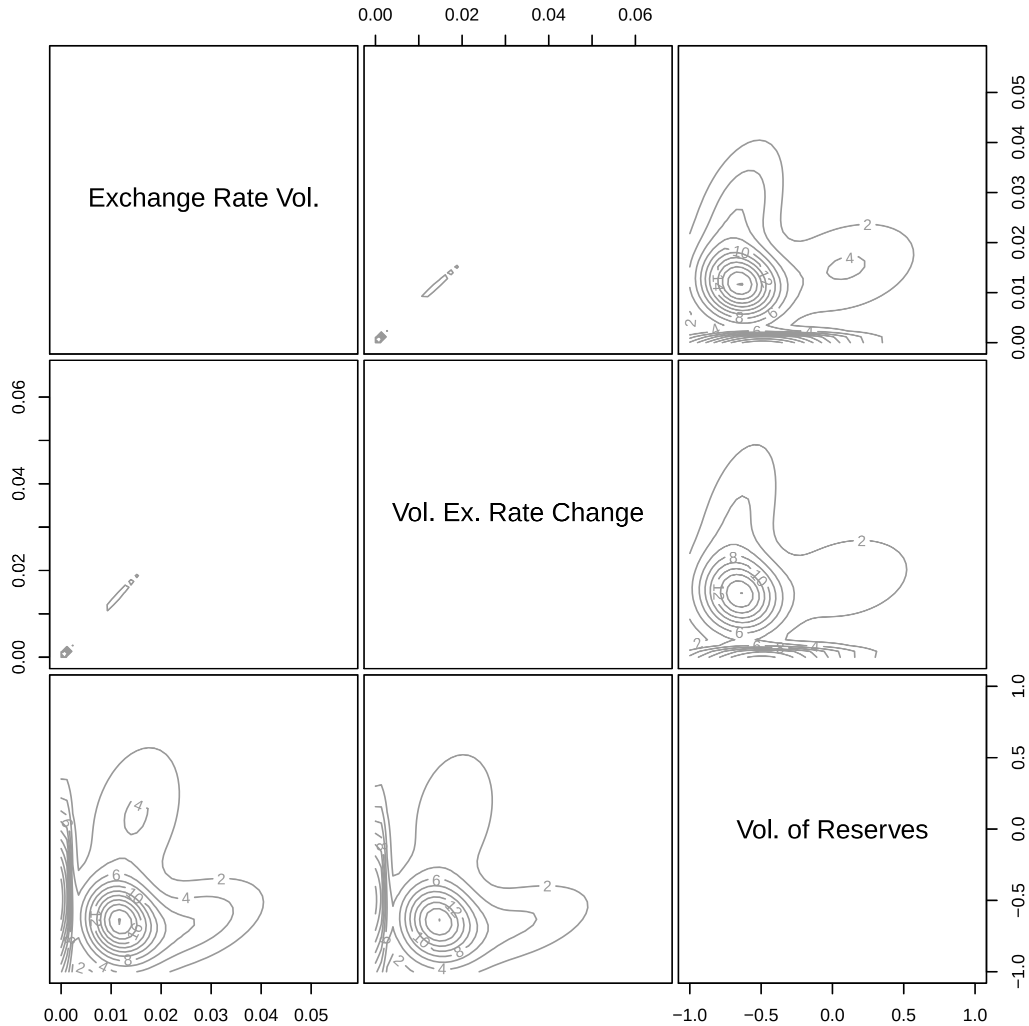


Figure B.14: Estimated density

B.5 Classification outcome

Table B.11: Probability of having a fix exchange rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA												81	44	81
ARMENIA								0	0	1	5	1		33
BRAZIL		12	4	5	4		1	12		5	5	17	1	3
CHILE	0	0	0	15		0	16	6	17	5	0	2	14	0
COLOMBIA	0	0	70	0	31	0	81	1	0	4		0	2	3
CZECH REP.	0	23	18	31	81		59	5	26	0	0	58	10	38
GHANA										4	1	2	75	4
GUATEMALA							81	100		50	30	15	46	81
HUNGARY			12	17	13	16	18	0	17	0	3	16		8
INDONESIA							0	29	3	5	0	38	70	41
MEXICO			5		0	29	26	14	31	5	0	16	0	6
PERU				81	87		19	79	12		4	82	72	
PHILIPPINES				69	14	29	78	0		0	62	28	79	80
POLAND	0	0	0	0	1	3	28	8	17	2		0	0	15
ROMANIA								78	16	0	0	79	79	81
SERBIA, REP. OF								45	17	0	3	0	17	0
SOUTH AFRICA		0		1	5	5	0	5	7	5	5	0	0	0
THAILAND		0	16	58	48	5	62	2	81	30	81	16	8	62
TURKEY								2	1	5	0	0	4	0

De facto regime based on highest probability for three possible arrangements: “Float" for perfectly floating exchange rates, “Inter" for intermediate or managed float exchange rate arrangements and “Fix" for rigid systems.

Table B.12: Probability of having an intermediate exchange rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA												0	1	0
ARMENIA								0	0	28	66	23		2
BRAZIL		46	70	66	68		85	38		66	66	35	85	74
CHILE	0	0	0	46		0	0	53	34	66	1	22	26	0
COLOMBIA	0	0	0	0	0	0	0	85	2	71		0	84	35
CZECH REP.	26	28	33	13	0		1	0	0	0	0	0	0	0
GHANA										72	87	25	2	70
GUATEMALA							0	0		6	20	37	9	0
HUNGARY			39	0	38	34	33	0	34	0	78	35		48
INDONESIA							0	19	0	65	6	14	0	13
MEXICO			0		0	20	0	37	18	65	3	35	0	63
PERU				0	2		19	0	33		0	0	0	
PHILIPPINES				0	36	33	0	0		0	0	23	1	0
POLAND	0	0	1	0	87	73	21	0	34	80		0	0	41
ROMANIA								0	16	0	26	0	0	0
SERBIA, REP. OF								8	33	0	74	0	34	5
SOUTH AFRICA		1		31	66	66	1	66	66	66	66	0	0	0
THAILAND		9	34	2	8	5	0	83	0	18	0	36	0	0
TURKEY								47	80	66	0	0	68	3

De facto regime based on highest probability for three possible arrangements: “Float" for perfectly floating exchange rates, “Inter" for intermediate or managed float exchange rate arrangements and “Fix" for rigid systems.

Table B.13: Probability of having a floating exchange rate arrangement

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA												19	55	19
ARMENIA								100	100	71	30	77		65
BRAZIL		43	26	30	28		14	49		30	30	48	14	23
CHILE	100	100	100	39		100	83	40	49	30	99	76	60	100
COLOMBIA	100	100	30	100	69	100	19	14	97	25		100	14	62
CZECH REP.	74	49	49	55	19		40	95	74	99	100	42	90	62
GHANA										25	12	74	23	25
GUATEMALA							19	0		44	50	48	45	18
HUNGARY			49	83	49	49	49	100	49	100	20	49		44
INDONESIA							100	52	97	30	94	48	30	46
MEXICO			95		100	51	74	49	51	30	97	49	99	31
PERU				19	11		62	21	55		96	18	28	
PHILIPPINES				31	50	38	22	100		100	37	50	21	20
POLAND	100	100	99	100	12	24	51	92	49	18		100	100	43
ROMANIA								22	68	100	74	21	21	19
SERBIA, REP. OF								47	49	100	23	100	49	95
SOUTH AFRICA		99		67	30	30	99	30	26	30	30	100	100	100
THAILAND		91	50	40	45	90	38	16	19	52	19	48	92	38
TURKEY								51	18	30	100	100	28	97

De facto regime based on highest probability for three possible arrangements: “Float" for perfectly floating exchange rates, “Inter" for intermediate or managed float exchange rate arrangements and “Fix" for rigid systems.

Table B.14: Inflation Targeting Regime

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ALBANIA												Hybrid	Flexible	Hybrid
ARMENIA								Flexible	Flexible	Flexible	Hybrid	Flexible		Flexible
BRAZIL		Hybrid	Hybrid	Hybrid	Hybrid		Hybrid	Flexible		Hybrid	Hybrid	Flexible	Hybrid	Hybrid
CHILE	Flexible	Flexible	Flexible	Hybrid		Flexible	Flexible	Hybrid	Flexible	Hybrid	Flexible	Flexible	Flexible	Flexible
COLOMBIA	Flexible	Flexible	Hybrid	Flexible	Flexible	Flexible	Hybrid	Hybrid	Flexible	Hybrid		Flexible	Hybrid	Flexible
CZECH REP.	Flexible	Flexible	Flexible	Flexible	Hybrid		Hybrid	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible	Flexible
GHANA										Hybrid	Hybrid	Flexible	Hybrid	Hybrid
GUATEMALA							Hybrid	Hybrid		Hybrid	Flexible	Flexible	Hybrid	Hybrid
HUNGARY			Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible		Hybrid
INDONESIA							Flexible	Flexible	Flexible	Hybrid	Flexible	Flexible	Hybrid	Flexible
MEXICO			Flexible		Flexible	Flexible	Flexible	Flexible	Flexible	Hybrid	Flexible	Flexible	Flexible	Hybrid
PERU				Hybrid	Hybrid		Flexible	Hybrid	Flexible		Flexible	Hybrid	Hybrid	
PHILIPPINES				Hybrid	Flexible	Flexible	Hybrid	Flexible		Flexible	Hybrid	Flexible	Hybrid	Hybrid
POLAND	Flexible	Flexible	Flexible	Flexible	Hybrid	Hybrid	Flexible	Flexible	Flexible	Hybrid		Flexible	Flexible	Flexible
ROMANIA								Hybrid	Flexible	Flexible	Flexible	Hybrid	Hybrid	Hybrid
SERBIA, REP. OF								Flexible	Flexible	Flexible	Hybrid	Flexible	Flexible	Flexible
SOUTH AFRICA		Flexible		Flexible	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Hybrid	Flexible	Flexible	Flexible
THAILAND		Flexible	Flexible	Hybrid	Hybrid	Flexible	Hybrid	Hybrid	Hybrid	Flexible	Hybrid	Flexible	Flexible	Hybrid
TURKEY								Flexible	Hybrid	Hybrid	Flexible	Flexible	Hybrid	Flexible

De facto regime based on highest probability for three possible arrangements: “Float" for perfectly floating exchange rates, “Inter" for intermediate or managed float exchange rate arrangements and “Fix" for rigid systems.

C Appendix: robustness tests.

Sample defintion: *pre*-period = 2004-2006 ; *post*-period = 2007-2008.

	Inflation		Excess Inflation		Credibility	
Constant (α_0)	1.63***	4.21***	2.31***	2.83***	-8.93***	-8.52***
	(.62)	(.81)	(.57)	(.45)	(2.11)	(2.37)
Dummy (α_1)	-1.68	-1.51**	-2.10**	-1.56**	6.19*	6.29*
	(1.04)	(.75)	(.95)	(.73)	(3.55)	(3.66)
X_{pre} (α_2)		-.49***		-.59***		.09
		(.13)		(.16)		(.20)
Groups	17	17	17	17	17	17
R-squared	.15	.58	.24	.61	.17	.18

	Inflation Vol. σ_{π_t}		Excess Infl. Vol. $\sigma_{\pi_t - \pi_t^\star}$		Credibility Vol. $\sigma_{(E_t[\pi_{t+1}] - \pi_t^\star)^2}$	
Constant (α_0)	.42	2.01*	.46	2.04**	129.38**	132.85*
	(.98)	(1.11)	(.93)	(1.04)	(63.72)	(69.71)
Dummy (α_1)	2.22	1.14	1.87	.88	16.65	13.53
	(1.65)	(1.53)	(1.56)	(1.42)	(107.25)	(112.79)
X_{pre} (α_2)		-.49**		-.45**		-.03
		(.21)		(.19)		(.18)
Groups	17	17	17	17	17	17
R-squared	.11	.35	.09	.36	.002	.003

	GDP growth		vol(GDP growth)		Interest Rate	
Constant (α_0)	-1.76***	-.92	.07	.59*	-1.29***	-.92
	(.59)	(.86)	(.53)	(.36)	(.48)	(.63)
Dummy (α_1)	.95	1.41	-.59	-.17	1.14	.98
	(.99)	(1.03)	(.90)	(.58)	(.86)	(.89)
X_{pre} (α_2)		-.13		-.39***		-.09
		(.10)		(.08)		(.10)
Groups	17	17	17	17	16	16
R-squared	.06	.16	.03	.63	.11	.17